<u>Artificial intelligence–enabled self-healing infrastructure systems</u>

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I, Lauren McMillan, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

ABSTRACT

Modern infrastructure systems are grappling with increased complexity and interdependence, struggling to predict and manage failures amid factors like population growth, urbanisation, rapid climate change, and economic challenges. While management methods remain fragmented, the rise of digitalisation and artificial intelligence (AI) offers a chance to adapt complex software-based approaches for infrastructure applications. One such approach is 'self-healing,' which anticipates and autonomously responds to system failures. AI's characteristics align well with self-healing concepts, making it a pivotal enabler. However, AI's current status in infrastructure management is unclear and there is a need to explore its application, learning from best practices in various sectors. Hence, this work presents a framework for self-healing infrastructure systems and explores the key components and processes necessary for implementation. Furthermore, in order to explore practical implementation, the framework is applied to leakage management in a water distribution system. Intelligent, data-driven solutions are proposed for each of the processes – anticipation, detection, and restoration – required to manage leakage as a self-healing system and these are trained and tested on a dataset of over 2,000 district metered areas (DMAs) managed by a UK water company. By offering a rapid and cost-efficient method for the identification of potential leakage, the benefits of this approach include enhanced resilience, optimised repair strategies, and improved consumer confidence, fostering sustainable demand-side behaviours. The contribution is a self-healing framework for management of leakage in water distribution systems, which demonstrates strong performance on the historical data provided and has the potential to be adapted to suit other contexts (including other types of infrastructure network). The findings of this research are of value to infrastructure owners and operators, regulators, and researchers, who see the potential in adopting a complex system perspective and recognise the role of AI in effectively applying this perspective to the management of real-world systems.

Keywords: infrastructure systems, self-healing, machine-learning, artificial intelligence, water systems, leakage

IMPACT STATEMENT

This study explores the concept of self-healing in infrastructure systems and the potential of AI as an enabler of such systems. These ideas are explored in their application to a case study in the water sector, addressing the challenge of leakage management in water distribution systems.

The academic contributions of this research include the development of a framework for self-healing infrastructure systems, allowing new and existing techniques to be mapped onto a system-based approach. The framework, as well as the complementary discussion on its components and steps for implementation, opens a new area of research on self-healing infrastructure systems, and the potential direction of future research in this area is also discussed. A thorough review on the use of AI in infrastructure systems offers additional insight into AI as an enabler for self-healing, explores the lessons that could be learned by taking a cross-sectoral view on AI application in infrastructure systems, and highlights several gaps in this field as areas for further consideration.

In the application of the framework to a water sector case study using machine learning methods, this study develops machine learning tools that, while applied to a specific use case, also demonstrate the wider potential of AI-based methods for self-healing systems and which could be adapted to suit other infrastructure applications.

From a policy perspective, the research emphasises the need for improved data collection, storage, and sharing standards within and across infrastructure systems. It highlights the importance of data formatting and management for achieving systemic self-healing. The study calls for mechanisms to balance privacy concerns with the benefits of data access for model development and promotes the sharing of insights generated from AI-based methods across different sectors to expedite progress towards self-healing systems and net-zero objectives. The findings also have policy implications for fostering digitalisation and enhancing workforce skills in intelligent infrastructure systems. The research encourages infrastructure operators to upgrade their systems and workforce to fully leverage the advantages of increased digitalisation while acknowledging the varying maturity levels in different sectors. The flexible approach presented allows for the substitution of more sophisticated methods as operators progress in their digitalisation journey.

The findings of this research are of value to infrastructure owners and operators, regulators, and researchers, who see the potential in adopting a complex system perspective and recognise the role of AI in effectively applying this perspective to the management of real-world systems. The developed case study on leakage is particularly pertinent for water supply and distribution companies and their contractors. From a water sector perspective, the research supports a shift towards a whole-system approach to leakage management, advocating for proactive strategies and considering anticipation and repair scheduling methods alongside leakage detection capabilities. By offering a rapid and cost-efficient method for the identification of potential leakage, the benefits to water companies include minimised downtime through improved resilience, optimised repair strategies to reduce water loss, and building consumer confidence, which will in turn promote sustainable demand-side behaviours.

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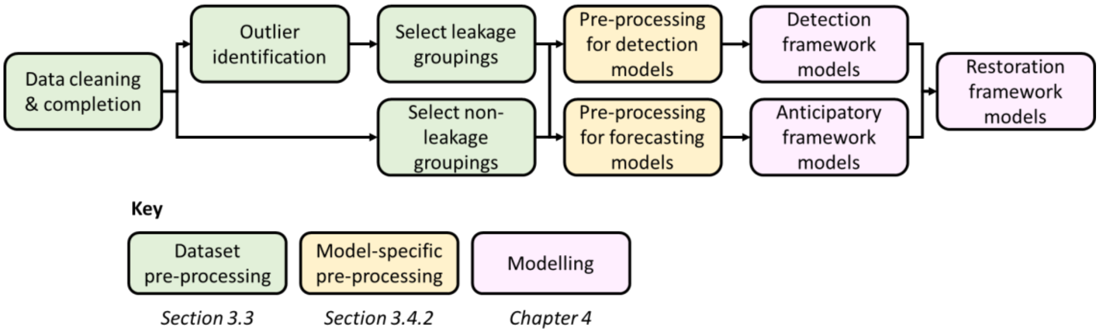
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Journal Articles

- McMillan, L., Fayaz, J., Varga, L., 2024. Domain-informed variational neural networks and support vector machines based leakage detection framework to augment self-healing in water distribution networks. Water Research. https://doi.org/10.1016/j.watres.2023.120983
- McMillan, L., Fayaz, J., Varga, L., 2023. Flow forecasting for leakage burst prediction in water distribution systems using long short-term memory neural networks and Kalman filtering. Sustainable Cities and Society 99, 104934. https://doi.org/10.1016/j.scs.2023.104934
- McMillan, L., Varga, L., 2022. A review of the use of artificial intelligence methods in infrastructure systems. Engineering Applications of Artificial Intelligence 116, 105472. https://doi.org/10.1016/j.engappai.2022.105472
- McMillan, L., Varga, L., 2022. Towards self-healing in water infrastructure systems. Proceedings of the Institution of Civil Engineers - Smart Infrastructure and Construction 1–9. https://doi.org/10.1680/jsmic.22.00006

Conference Papers

- McMillan, L., Fayaz, J., Varga, L., 2022. Machine-learning-based health monitoring and leakage management of water distribution systems. International Conference on Evolving Cities (ICEC), Southampton, UK. https://doi.org/10.55066/proc-icec.2022.37

1. INTRODUCTION

Infrastructure systems provide crucial services such as energy, water, transport, and telecommunications. As cities expand and infrastructure networks serve growing numbers of people, these systems have become increasingly complex. Additional complexity, and the associated interdependencies between networks, increases the difficulty of predicting system failure and the propagation of failure throughout the network [1]. In order to effectively manage infrastructure systems, systemic approaches, which address failures within the wider context of a complex network, are required.

This research seeks to explore how self-healing, a systemic approach to the management of software-based systems, could be effectively applied to infrastructure systems. The concept of self-healing is introduced, and the key processes of a self-healing system are described. The types of threats and failures present in software-based systems and infrastructure systems are then explored, to establish how a self-healing approach might be adapted from the former to the latter.

Artificial intelligence (AI) is a rapidly expanding field of research, with huge strides made in recent years in the accuracy, speed, and sophistication of artificially intelligent methods. Machine learning is a major subfield of AI, underpinning AI systems and allowing a system to ‘learn’ from data independently in order to improve the system or accomplish an assigned task [2] [3]. While infrastructure systems have been slower to adopt AI and machine learning methods than other sectors such as the technology sector, the push for improved digitalisation in infrastructure systems in order to make better use of such methods is now well underway [4] [5]. There is a need to explore how AI has been implemented in infrastructure systems to date, as there is an absence of review literature in this area [6], in order to better understand which methods are best suited to the variety of applications seen across infrastructure systems [7]. There is significant opportunity for learning across infrastructure sectors, as many share common challenges and all represent complex and interdependent systems. This research will undertake a comprehensive examination of the current state of the art of AI in infrastructure systems. It will take a cross-sectoral approach, analysing the methods employed and the specific purposes to which they have been applied. By exploring various sectors and the intersections between them, this thesis aims to gain insights into the diverse range of AI applications in infrastructure systems and identify common trends and best practices.

Due to the ability of machine learning methods to learn from data in the system and generate insights autonomously, without the requirement for human intervention throughout, the potential for machine learning as an enabler for self-healing systems is evident. Rather than simply executing the instructions of human operators, machine learning can allow infrastructure systems to adapt to potential failure risks by modelling the complexities of the system and generating a response that is based on data-driven insight. Depending on the system and methods, machine learning can be used to forecast future scenarios, monitor the health of a system, and optimise system repair, among many other applications [8] [9] [10] [11]. Given the components of a self-healing system, which are explored in the following section, machine learning methods are the obvious choice for establishing rapid and comprehensive self-healing approaches for the management of infrastructure systems. To establish the potential of machine learning for self-healing infrastructure systems, this research presents the case study of a self-healing framework for leakage management in water distribution systems, which employs several machine learning methods for crucial self-healing processes.

1.1 ORIGINS AND ELEMENTS OF SELF-HEALING SYSTEMS

1.1.1 SELF-HEALING STATES AND PROCESSES

Self-healing has its origins in software-based systems, where IBM's autonomic computing initiative outlined their vision of 'self-managing' systems [12]. Seeking to shift the management of increasingly complex computational systems away from error-prone human operators, IBM proposed integrating this responsibility into the system itself. Self-managing systems were further defined by four sub-characteristics; self-configuring, self-healing, self-optimizing, and self-protecting, with self-healing described as the ability of the system to 'discover, diagnose, and react to disruptions' [12]. While true self-healing is performed in the absence of human intervention, systems that require some degree of interaction with an external agent can instead be described as assisted-healing systems [13]. Self-healing terminology remains largely within the realm of computing systems, where various frameworks and architectures to enable self-healing have been explored [14] [15] [16]. However, self-healing has begun to make its way into the field of infrastructure systems, particularly energy systems [17] [18] [19], as is explored in section 1.3.

Self-healing cannot be possible without self-awareness. The ability of a system to act, either to prevent or react to failure, is dependent upon understanding that the system is behaving in such a way that intervention is required. Being able to detect and define the state of a system at a given time is thus crucial to self-healing. Conveyed in Figure 1, which is adapted from [13], systems can be categorised as being in one of three states; normal, degraded/damaged, and broken. In a normal – or healthy – state, a self-healing system will be able to provide resources or services at standard operating levels. What constitutes 'normal' is not always immediately evident, and may fluctuate under variable operating conditions. In the degraded or damaged state, a self-healing system must be able to specify a threshold at which restorative actions are deemed necessary. This threshold may be defined as bounded acceptable values (possibly provided by standards or regulations), a percentage deviation in conditions, or the occurrence of measurable unacceptable behaviours within the system. In the broken state, the system is no longer able to provide acceptable service, and actions to restore system function must be identified and prioritised.

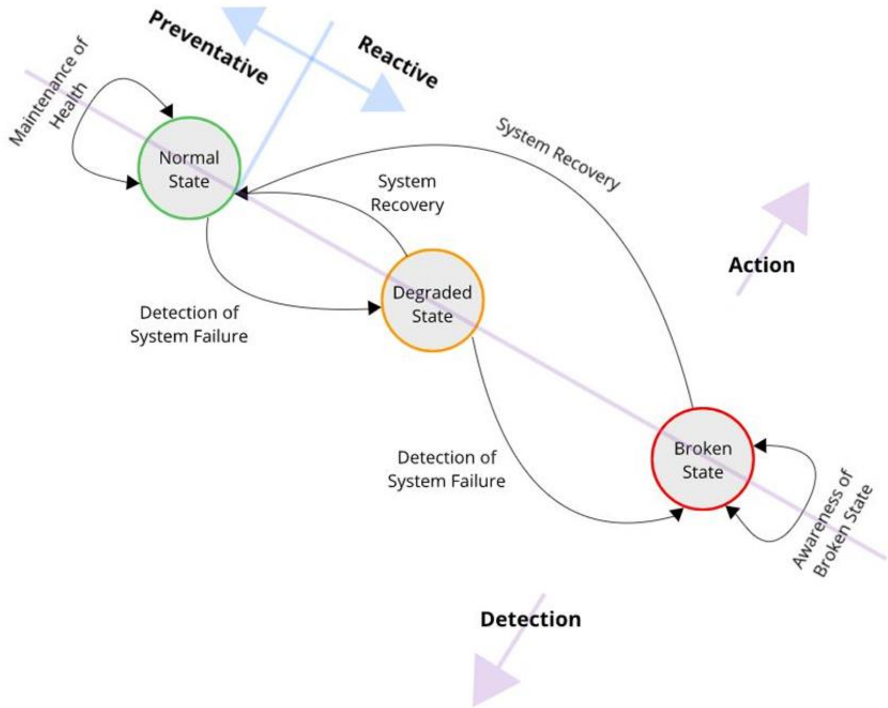


FIGURE 1: SELF-HEALING SYSTEM STATES AND PROCESSES. ADAPTED FROM [13].

While the status of a self-healing system at a given time can be described by its state, the processes by which a system maintains its current state or moves between states fall into three categories: detection, preventative action, and reactive action [20]. In the transition from normal to non-normal states, the system must detect that performance has deviated from normal levels, in order to trigger a self-healing response. This process of detection comprises of monitoring the system and recognising when functionality is compromised. In instances of sudden service loss, the transition to a broken state can be almost instantaneous. An example of this would be when natural disasters sever power lines or broadband cables, burst water pipes, or block roads or railways. However, the transition from a normal state to a broken one can also be a progressive degradation. In this case, the system experiences a 'fuzzy zone' of deterioration, in which it can be difficult to define a discrete line between healthy and unhealthy states [13]. Maintaining a healthy state requires not only an ongoing process of detection, but proactive interventions to prevent any unacceptable change in system parameters that might cause degradation in system performance. Any actions undertaken to prevent deviation from the normal state can be described as preventative, as these are implemented before system performance is compromised. Should such measures fail to prevent transition to a damaged or broken state, the return to a healthy state is achieved through interventions that enable system recovery. Such actions are reactive, as they follow a degradation of system service.

1.1.2 Self-healing vs decision support

While decision support systems (DSS) can facilitate self-healing processes, the two types of system are not interchangeable. Traditionally, DSS have been thought of as a support to a human decision-maker, rather than as a replacement, and the human-user interface is considered an important component of DSS [21]. The decision support typically offered by DSS can be described as passive, with the outcome of the decision-making process ultimately down to the system user. Self-healing systems, however, have the potential to deliver active decision support; they are able to detect and respond to failure in the absence of human intervention [13]. With well-developed system architecture, self-healing systems may also have the capacity to select an optimum remediation strategy and prioritise certain components in repair scheduling [13]. In complex, inter-connected systems, taking the initiative from the user and returning it to the system itself can enable a faster, more effective response to disruption.

This is not to say that DSS cannot play a role in enabling self-healing, particularly in sectors where self-healing systems are in their infancy, with human intervention not yet eliminated from the system. Assisted-healing systems share many core elements with DSS, including the need to detect and define system failure. It is in their approach to active interventions where the two differ, with DSS typically offering advice to a human decision-maker, while assisted-healing systems are able to make their own decisions but require a human agent to implement their chosen course of action [13]. With these two concepts so closely linked, and while self-healing terminology remains uncommon in many fields, DSS may offer some of the most valuable insights into the progression of self-healing ideas in infrastructure systems.

1.2 THREATS AND FAILURES IN A SYSTEM

1.2.1 INTRODUCTION

In order to heal itself, a system must first be able to identify when it needs healing. Detection of failure requires that a system not only be able to be accurately modelled or otherwise represented, but that this representation be able to identify ‘failure’ in the system [13]. This section further explores the threats facing infrastructure systems and the types of failure that these can lead to.

1.2.2 THREATS

Threats are anything that has the potential to disrupt the service of a system. Infrastructure systems face a variety of threats, which vary in origin, nature, and impact. These threats have to potential to cause system failures, which also differ significantly in scope. In order to establish an effective response to such failures, classification of the threats and the corresponding modes of failure is an important task in self-healing systems.

Several works have sought to categorise the threats facing infrastructure networks. Little [22] broadly divides these threats into those in the natural realm and those originating from anthropological sources. Natural hazards comprise droughts, dust storms, earthquakes, extreme cold, floods, fog, heat, hurricanes, landslides, lightning, hailstorms, ice/sleet, snow avalanches, snowstorms, tornadoes, tropical storms, tsunamis, wildfires, wind, and volcanoes [23], while non-natural hazards include both malicious threats, such as terrorist acts, as well as poor infrastructure design or management, e.g. design faults, excessively prolonged service lives, aging materials, and inadequate maintenance [24].

Robles et al. [25] recognise the distinction between intended and accidental threats by classifying hazards into three categories; natural threats, human-caused, and accidental or technical. Human-caused threats may include cyberattacks, rioting, product tampering, explosions and bombing, while accidental and technological threats include such issues as transportation accidents and failures, infrastructure failures, and hazardous material accidents.

Rehak, Martinek, & Růžičková [26] go beyond the umbrella term of 'natural' hazards, recognising that there are more distinct sub-classes within natural threats, and grouping threats into five categories;

- Climatological threats – these include exceptional weather events, such as tornadoes, hurricanes, and heavy snowfall, and weather-induced hazards, including floods and fires.
- Geological threats – these include earthquakes, volcanic activity, and landslides.
- Biological threats – these include bacteria, viruses, and toxins that can disable or kill people, animals, and crops. This category also includes pandemics.

- Technological threats – these include technological emergencies such as radiation emergencies, hazardous chemical spills, flooding caused by damage to hydraulic structures, widespread disruptions to engineering networks, public water supply emergencies or major road, rail, or air traffic accidents.
- Criminal threats – these include cyberattacks, terrorism, and armed conflict.

The threats confronting infrastructure systems have the potential to trigger events/emergencies that may generate failures. It has been suggested that these proposed categories of threat fit discretely into the broader headings of natural emergencies (climatological, geological, and biological threats), intentional anthropogenic emergencies (criminal threats), and unintentional anthropogenic emergencies (technological threats) [27]. However, these categories are describing the origins of emergencies, rather than the specific nature of the emergency itself.

As many threats exist within complex systems, it is not always possible to draw such a direct link between their causes and their characteristics. For example, acid rain, while climatological in nature, is often a result of, or exacerbated by, human activities. Indeed, many extreme weather events have seen an increase in severity and frequency as a result of climate change [28], which has been attributed, in large part, to an increase in anthropogenic fossil fuel usage [29]. While knowledge of the origins behind threats to infrastructure systems is valuable, these origins are not always as straightforward as they may seem, due to the complexity of infrastructure networks and their integration with natural and industrial systems.

In real-time computational systems, threats that go on to impact the system are often described as faults. Not all threats will necessarily create faults, and not all faults will go on to cause failures. Fault prevention seeks to stop threats from becoming faults, while fault tolerance is the ability of a system to avoid service failures in the presence of faults. Fault classification, as in threat classification, does consider the origin of faults, but as just one of many categories. Avizienis et al. [30] present eight perspectives from which faults can be considered, termed 'elementary fault classes'. These are shown in Figure 2.

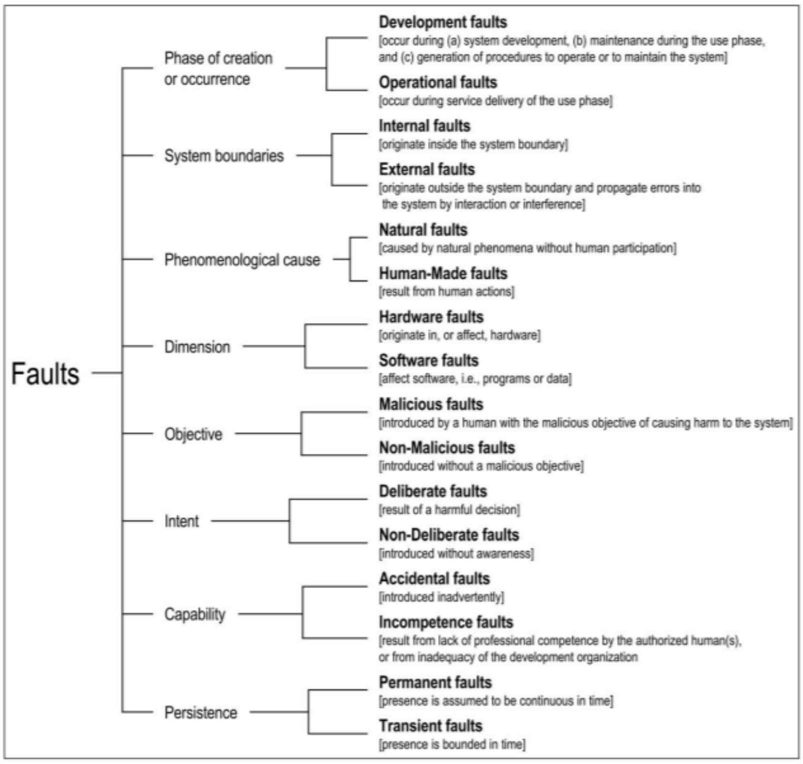


FIGURE 2: ELEMENTARY FAULT CLASSES. SOURCE: [30].

Certain combinations of these elementary classes are more prevalent than others, while some combinations are impossible. For example, natural faults cannot be classified by objective, intent, and capability. As such, the authors propose 31 likely combinations, which correspond to three major groups (with partial overlap) as shown in Figure 3. These broader groupings are [30];

- Development faults – these include all fault classes occurring during the development stage of the system.
- Physical faults – these include all fault classes that affect hardware.

- Interaction faults – these include all faults originating outside of the system boundary (external faults).

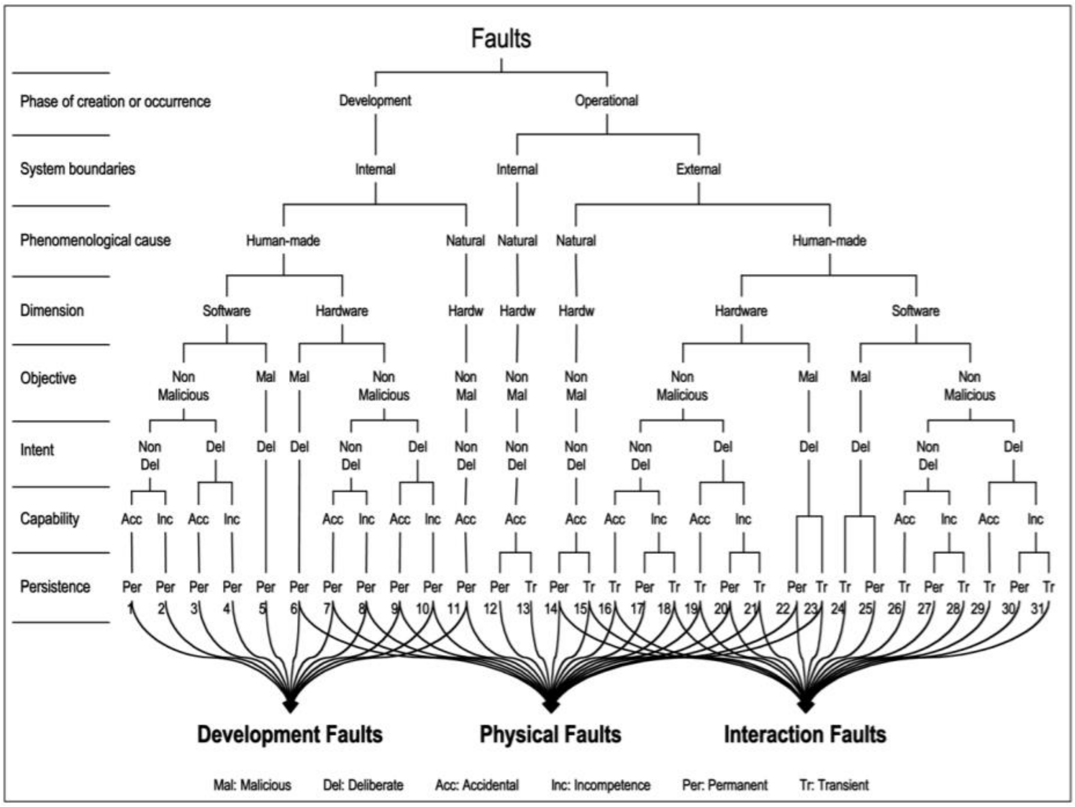


FIGURE 3: FAULT CLASS COMBINATIONS. SOURCE: [30].

While these classes stem from a computational systems' perspective, their broad nature enables them to be effectively applied to infrastructure systems. For example, 'hardware' in the context of the transport sector may represent physical infrastructure like railway lines, tube stations, planes, airports etc., while 'software' may represent control systems, such as air-traffic control or traffic light control systems. As cyber-physical systems are increasingly integrated into infrastructure systems, the adoption of computational systems-based classification methods may ensure that the increasing digitalisation of infrastructure can be represented in threat analysis.

1.2.3 FAILURES

A failure is an event that denotes a deviation between the actual service provided by the system and the specified or intended service, occurring at a particular point in real time [31]. As with threats, failures can be classified in several ways.

Perhaps the simplest method of failure classification focuses on the nature of the failure as experienced by the user and uses just two groupings: value/content failures, and timing failures. This distinction originates in computational systems, where value/content failures result in the user being provided different content (or a different value) at the system interface than the content intended as the system's function. On the other hand, a timing failure means that a value is presented (i.e. a service is provided) outside the specified interval expected of the system [30], [31]. While this definition focuses on the exchange of information that underpins computational systems, it is relatively easy to expand this definition to infrastructure systems. Put simply, timing failures represent system delays – the user doesn't get their service when they expect it – and content failures represent a system functioning incorrectly – the user gets the wrong service, no service, or a poor-quality service.

While system delays are somewhat self-explanatory, content failures in infrastructure systems encompass a much broader spectrum of failures. This includes damage to any physical assets that results in a loss of service, such as broken energy cables leading to power outages, as well as any issues with system management or operation that lower the quality of system service to an unacceptable level. An example of that latter could be treated water supplies having above-regulation pollutant levels.

Looking again to computational systems, with a particular focus on distributed systems, a distinction can be made between omission, arbitrary, and timing failures, with the latter as described above. Omission failures occur when the system fails to complete an action necessary for service provision, resulting in the absence of that service. Arbitrary failures, also called Byzantine failures in the field of computational systems, arise when a system arbitrarily omits intended processing steps or takes unintended processing steps [32]. Arbitrary failures present a unique challenge in that they cannot be detected through querying, as the system may arbitrarily decide to respond positively, or fail to respond at all. This leads to another distinction between failures, based on how users perceive the system; consistent and inconsistent failures. With consistent failures, the incorrect or degraded service is perceived identically by all system users. However, inconsistent failures, which are synonymous with arbitrary or Byzantine failures in distributed computational systems, result in some or all system users perceiving failure differently, with the potential for some users to actually perceive correct service [30]. It is perhaps this distinction in how users perceive failure that best maps to failures in infrastructure systems; a failure can impact all users in the same way, or lead to different users experiencing different types or levels of service. An example of the former would be a signal failure causing all services to or from a given station to be cancelled, while an example of the later would be solar or wind generators (distributed renewable sources of energy) in a decentralised energy grid experiencing intermittent fluctuations due to varying weather conditions. Users connected to the affected renewable sources may intermittently experience fluctuations in the energy supply, perceiving a degraded service. However, users connected to other renewable sources with stable conditions continue to receive consistent power.

Research on failures in real-time systems has proposed two further groupings to complement those already discussed [31]. In this classification, shown in Figure 4, failures can be sorted by nature, perception, effect, and frequency (termed ‘oftenness’). Incorporating the ideas behind failure categories discussed above, the nature of failure differentiates between value/content and timing failures, while the users’ perception of failure can be classified as either consistent or inconsistent. An alternative class, failure effect, is concerned with the impact of a failure on its environment. A failure is benign if it results in costs of the same order of magnitude as loss of normal system utility. A malign failure, however, can result in costs that are orders of magnitude greater than the normal system utility. Costs are not strictly financial; a malign failure may cause catastrophic events that result in significant injury or loss of life, such as plane or train crashes. The properties of the application of the system therefore determine whether a failure is benign or malign. A final failure category, oftenness, describes the number of times failure occurs in a given time frame. A single failure occurs only once, and a permanent failure is a single failure after which the system's service is halted or compromised until restorative action takes place. By contrast, transient failures occur when the system continues to operate after a failure. Transient failures that take place with some regularity can be called intermittent failures [31].

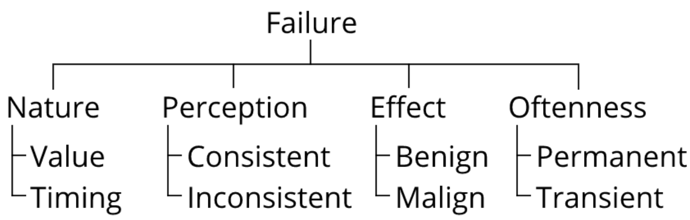


Figure 4: Failure classification. Source: [31].

Like their computational counterparts, infrastructure systems are becoming increasingly complex. The growing digitalisation of critical infrastructure has intensified the levels of interconnectedness between networks which also interact with the larger economic, environmental, and societal systems within which they reside [33]. This creates interdependencies between systems, which can increase the risk of failure across system boundaries and significantly affects how failure travels through a network. Groupings have been proposed for assessing the criticality of infrastructure systems, where criticality can be defined as the decisive capabilities needed to prevent, mitigate, or compensate for failures due to infrastructure impairment. The general characteristics proposed for criticality in infrastructure systems are [34];

- Critical proportion – including system load, capacity, redundancies, and interdependencies, as well as number of users, assets, and nodes.
- Critical time – including failure duration, timing of failure, and time to repair, replace, restore, or react to failure.
- Critical quality – including the quality of goods or services provided, public trust in quality, and the social or cultural significance of an asset or system.

Though not classifying failure directly, this approach recognises the criteria that a system must satisfy in order to function at healthy levels. Should a system fail to meet a required critical value, this could be deemed either a failure or a vulnerability to failure, depending on the nature of the criteria.

Perhaps the most established approach to failure classification in infrastructure systems is rooted in the recognition of interdependencies between infrastructure networks [1]. An interdependency occurs when there exists a bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other. Interdependent systems are highly interconnected and mutually dependent in complex ways, which can increase the risk of failure across systems. Interdependencies significantly affect how failure travels through a network, and Rinaldi et al. [1] were the first to classify the basic types of failure propagation in critical infrastructure systems;

- Cascading failure – occurs when a disruption in one infrastructure causes the failure of a component in a second infrastructure, which subsequently causes a disruption in the second infrastructure. For example, electric power failures can generate failures in other infrastructure systems that rely on electricity to function, such as electrified rail.

- Escalating failure – occurs when an existing disruption in one infrastructure exacerbates an independent disruption to a second infrastructure, generally in the form of increasing the severity or the time for recovery or restoration of the second failure. For example, disruption to a telecommunications system may be escalated by separate disruption to a road network being utilised to transport equipment or repair crews.
- Common cause failure – occurs when two or more infrastructure networks are disrupted at the same time: components within each network fail because of some common cause. Components from multiple infrastructure networks could be affected simultaneously, either because the components occupy the same physical space or because the root problem is widespread. For example, natural disasters can damage multiple infrastructure systems.

1.3 SELF-HEALING IN INFRASTRUCTURE SYSTEMS

1.3.1 ADOPTION OF SELF-HEALING IN INFRASTRUCTURE SYSTEMS

The management of complex infrastructure networks, as for complex software-based systems, presents a significant challenge for human operators, who may struggle to anticipate the effects of interdependencies on failure propagation throughout the system. Building self-healing capacity into such a system has many obvious benefits, from the removal of human error to a swift reduction in response times.

The energy sector has already begun to embrace this approach, with self-healing a key characteristic of the smart grid [35]. With so many services dependent on a stable power supply, the consequences of failures in power grids have never been greater. A self-healing smart grid is able to detect abnormalities, reconfigure the system in order to isolate disturbances, and minimise disruption by reducing outage frequency and minimising outage length. Self-healing also gives the smart grid end-to-end resilience, with the ability to detect and override human errors that may have otherwise resulted in outages [17].

The water sector offers further examples of complex and highly interdependent systems, with dynamic interactions between constructed infrastructure networks, the physical environment, and societal pressures. This can result in multi-objective, multidisciplinary challenges, giving rise to unpredictable and emergent behaviours [36]. However, a self-healing approach to system management is yet to be widely adopted in the water sector. Vertical integration within water supply and distribution networks, a huge proportion of assets being buried underground, lack of accurate geospatial data, and limitations of legacy infrastructure are additional challenges faced by this sector that may have contributed to this slower uptake.

The failure threshold in infrastructure systems can be hard to define but should be given explicit consideration when adopting a self-healing approach. The failure threshold may be set by operators and could be in the form of a required level of service, a percentage of the network being operational, a number of customers served etc. The failure threshold may, however, be a property of the models used for system management. For example, the failure criteria for many anomaly detection methods, including machine learning methods, can depend on a number of hyperparameters and features of the training dataset [37]. These hyperparameters, once tuned, can provide better accuracy than operator-selected thresholds for failure in many cases where there is a high degree of system complexity and many variables to consider. However, other factors such as budget and resource availability may result in the need to adjust the failure threshold by adding additional criteria. For example, repairing of road surface failures may choose to neglect minor defects in favour of fixing more severe cracks or potholes, if the budget does not allow all defects to be addressed.

1.3.2 Self-healing in a digital ecosystem

Given that appropriate self-healing interventions have a massive dependency on accurate, timely, and secure information, the digitalisation of infrastructure systems provides both some of the greatest challenges and opportunities for the adoption of self-healing techniques.

Increased digitalisation allows for the possibility of a real-time, or ‘right time’, connection between the infrastructure system and theoretical and mathematical models. ‘Right time’ connections provide data at a sufficient rate to satisfy the needs of the system, for example reservoir levels may be supplied only daily during typical weather conditions, but more frequently during storm events. Access to a reliable data connection, typically provided by a network of sensors, allows the infrastructure system to be accurately modelled in its present state. This data can also be used in scenario modelling, to anticipate potential failures and identify vulnerabilities in the system. However, implementation of the knowledge and insights generated by such modelling is currently limited. For example, in the water sector specifically, at present a human is almost always in the loop to facilitate the connection between the outputs of the system model and the physical system itself. This common digital set-up is illustrated in Figure 5. What digitalisation does offer, however, is the opportunity to minimise the risk associated with this human link in the chain by using data science techniques to integrate decision making capacity into the system model.

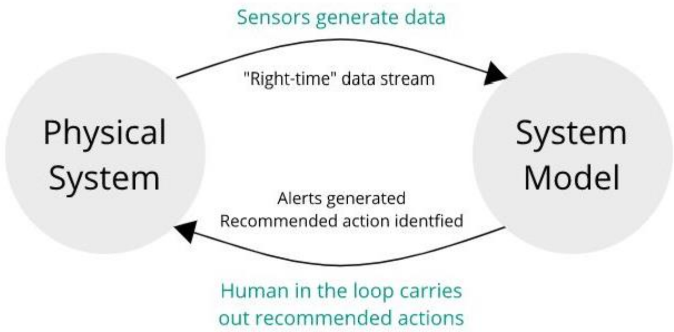


FIGURE 5: A COMMON DIGITAL SET-UP FOR INFRASTRUCTURE SYSTEMS.

An assumption made by many of the proposed techniques for infrastructure management in the water sector is the availability of accurate and complete data. Research that utilises real-time data has found that this is not always the case, with one study on leakage detection finding that data corruption issues/logger failures were responsible for 8.2% of alerts issued [38]. With buried networks like water distribution pipelines, access to repair or replace sensing hardware is costly and time-consuming. As such, data pre-processing methods are often employed to improve the quality of data inputted into models [39]. Unreliable data can, in some cases, increase the responsibility of the human in the loop, who may have to use their discretion to judge whether or not an alert was made in error. In such circumstances, the expertise of the human in the loop is key to success. A healthy digital ecosystem, while it may benefit from discretionary manual override or input capacity [40], seeks to limit the requirement for in-the-moment human judgement during complex decision-making, both by ensuring reliable data access and by developing models which are able to handle imperfect or unexpected data, increasing confidence in model outputs.

1.4 ARTIFICIAL INTELLIGENCE FOR SELF-HEALING IN INFRASTRUCTURE

Self-healing refers to the ability of a system to autonomously detect, diagnose, and respond to failures or disruptions, minimising their impact and restoring functionality without the need for human intervention [13] [14]. Infrastructure systems are complex due to their multiple interconnected components, emergent behaviours, large scale, and dynamic environments [41]. The uncertainties, non-linearities, and feedback loops within these systems make them challenging to predict and manage effectively. Human behaviours, cybersecurity concerns, interoperability issues, and resource constraints further add to the complexity, making it difficult to understand and predict how failure can manifest and propagate through such systems [27]. It is therefore challenging for infrastructure systems to make timely and considered decisions in response to threats using human-driven management alone. Such complex and interdependent systems can benefit significantly from a self-healing approach.

AI could play a crucial role in developing and enabling self-healing capabilities in infrastructure systems. The AI revolution, which is bringing about great advances in machine learning methods, offers significant opportunities to capitalise on the growth of digitalisation and has the potential to enable the ‘system of systems’ approach required in increasingly complex infrastructure systems. Machine learning can be considered a major sub-field within the broader field of AI and represents much of the application of AI to digital-based systems. Machine learning methods enable machines to learn and infer from large volumes of data [42]. By leveraging machine learning methods, infrastructure systems can often achieve higher levels of performance than many traditional manual or rule-based approaches [43]. Compared to traditional methods, machine learning-based approaches often bring scalability, efficiency, and adaptability to infrastructure systems. Depending on the algorithms used, machine learning-powered systems can adapt and learn from new data, continuously improving their performance and adaptability to changing conditions [44]. By automating and optimising various processes, AI can reduce the opportunity for human error and enable more efficient allocation of time and resources, resulting in cost savings and improved system performance. As infrastructure systems become increasingly interconnected, complex, and digitalised, machine learning will be crucial in providing and maintaining services that ever-increasing numbers of people depend upon every day [45].

While infrastructure systems generate and handle varying levels of data in terms of quantity and quality, it is certainly true that such systems are becoming increasingly digitalised [46]. This is a crucial step towards providing the data necessary for machine learning methods to drive self-healing processes for these systems. Improvements in sensing technologies and the rise of the 'Internet of Things' has seen more data generated by infrastructure systems than ever before, and the handling of 'big data' presents its own challenges and complexities. Big data is commonly defined as having three attributes; volume, variety, and velocity [47]. Volume considers the amount of data generated, which can go beyond terabytes and petabytes. Variety means that the data provided can be both structured data and unstructured data, while velocity is concerned with the regularity with which data is generated, with many big data systems having near-continuous streams of the data [5]. In infrastructure systems, data is now available from many new sources, including GPS, wireless devices, sensors in supply and distribution networks, and communication generated by machine-to-machine interactions [48]. Data in infrastructure systems can be rapid, unstructured, and available in many different formats, which is difficult to deal with by traditional methods. It is therefore crucial that new methods for infrastructure system management are able to suitably process and utilise big data [5]. If implemented effectively, machine learning methods have significant potential in this area.

The potential of AI to deliver self-healing infrastructure systems goes beyond machine learning's ability to handle 'Big Data'. In infrastructure systems, AI, and particularly machine learning and computer vision methods, can be used for improved system health monitoring, which can facilitate the 'self-awareness' necessary for a self-healing system [49]. In the context of self-healing systems, this awareness is primarily in terms of the system state, and so can also be considered 'state-awareness'. The first step towards self-healing must be accurate assessment of the current state of a system, so that the system can know whether actions are required to either maintain or restore system health. Machine learning methods can analyse large volumes of data collected from sensors, monitoring devices, and other sources in infrastructure systems. By continuously monitoring and analysing this data, machine learning algorithms can detect anomalies or identify changes to system characteristics that indicate changes to the state of the system. An example in infrastructure systems would be the use of AI for improved monitoring of water quality at various stages of the supply and distribution chain, in order to ensure that certain chemicals are kept within acceptable levels for customer consumption [11] [50]. If levels remain well within the accepted range defined by industry standards, the system could be considered healthy, while if levels fall outside of the accepted range, the system may be considered to have suffered a failure. It may be that, should levels shift towards the upper or lower bound of acceptability, preventative actions are necessary to stop the slide into a failed state, and so knowledge of the system state is critical even before a failure has occurred. The high levels of accuracy offered by AI in both system monitoring and trend detection thus present a promising solution to the challenge of self-awareness in infrastructure systems.

At the component level, identifying potential changes in the health of a component can ensure the continued health of the system even if individual components are damaged. Both machine learning and computer vision have been applied to structural health monitoring of infrastructure components. For example. by analysing data, including camera footage, from wind turbines, machine learning algorithms can detect small changes in turbine blades that could indicate damage to the blade [51]. By detecting small changes early, the component can be flagged as degraded and replaced before there is any impact on the turbine's ability to generate power, ensuring the overall system remains at a healthy state.

The predictive capabilities of machine learning can be used to identify potential threats or failures in the system and predict system vulnerabilities, dovetailing well with the anticipatory process of self-healing systems. This proactive approach can allow infrastructure systems to anticipate and prevent issues before they escalate, contributing to self-healing through the triggering of preventative maintenance actions. An example of this would be forecasting demand in infrastructure systems such as energy [52] and water networks [53] to ensure that resources are best allocated to meet expected demand, or that measures can be put in place to reduce demand. In energy systems, a forecasted surge in demand may result in the use of hydroelectric resources to free up additional capacity or the purchasing of additional capacity from other sources such as from abroad, in order to keep the system healthy. If resources are limited, the preventative actions taken may include demand reduction methods, such as hosepipe bans in the water sector. Although this can represent a temporary degradation in service quality, it may be necessary to prevent further degradation of the system to a broken state in which service levels are further reduced to unacceptable levels. Machine learning's forecasting abilities are well-established [54], outperforming traditional methods in numerous applications [55] and certain machine learning and deep learning-based methods able to handle the complexities of nonlinear relationships [56]. The adoption of machine learning for forecasting in infrastructure systems can therefore enable the development of predictive models that anticipate potential failures based on historical data, patterns, and machine learning algorithms [44]. By using predictive models to forecast the likely future state of a system, infrastructure systems can proactively address vulnerabilities, schedule maintenance activities, and optimise resource allocation. This enhances the self-healing capabilities of infrastructure systems predominately through the anticipatory process but also facilitates improved early-warning to prevent system progression to the broken state.

During failure scenarios, AI can enable real-time decision-making by processing data rapidly and providing insights to guide actions. When a failure or disruption occurs, machine learning algorithms can quickly assess the situation, evaluate available options, and determine the most appropriate response. Even in systems where human intervention may be necessary to carry out the proposed action, machine learning can take on the role of decision-maker, informing the human-in-the-loop of prioritised tasks that have been selected through rapid data analysis. An example of this is the task of fault diagnosis of vehicle on-board equipment in high-speed rail systems. The faults of such systems are usually uncertain and complex, and current fault diagnosis methods rely heavily on manual judgement in real-world operations, which is inefficient and highly susceptible to human error [57]. The application of machine learning to this task ensures a greater likelihood of correct fault diagnosis, which means any necessary repair resources or replacement parts can be more rapidly sourced, even if a human is still required to manually fix the identified fault. This real-time analysis and decision-making enable infrastructure systems to take rapid corrective measures, minimising downtime and mitigating the impact of failures. Fully self-healing systems may remove the need for human intervention altogether, although for this to be realised at a widespread level in infrastructure systems, improvements in the development and implementation of robotics will be necessary.

In some systems, particularly telecommunication networks and systems with automated control systems, AI can also enable autonomous decision-making and control mechanisms in infrastructure systems [58]. By combining AI with automation technologies, systems can respond to failures or disruptions in real-time without human intervention [59]. For example, in software defined wireless networks, deep learning can be used for network traffic control and routing, identifying the best path combination for packet forwarding in switches [60]. In this example, network traffic can be rerouted by the system itself, and so the restorative action is provided by the system and not a human-in-the-loop. AI algorithms can trigger the rerouting of resources, the activation of backup systems, or the isolation of affected components to minimise the impact of failures and maintain essential services.

In summary, AI, and machine learning in particular, holds immense potential for developing and enabling self-healing capabilities in infrastructure systems. Machine learning can be used to provide infrastructure systems with the ability to anticipate, detect, and, in some cases, respond to failures autonomously, enabling the main processes of self-healing. Furthermore, machine learning's adaptability and capacity for continuous learning enable systems to evolve and improve over time, developing resilience in the face of changing conditions. In time-sensitive sectors like healthcare, energy, and transportation, self-healing systems equipped with AI could make split-second decisions to avert potential disaster. Such capabilities significantly reduce human intervention, which is essential in situations where a rapid response is critical. Infrastructure systems often face time-sensitive threats, and the impacts of failure can be very severe. The potential of AI in infrastructure systems remains to be realised on a widespread level, however, and there remain many barriers in the way to successful implementation of machine learning tools in many infrastructure systems, some of which will be explored in this thesis.

However, as interest in AI continues to grow, research into its application to infrastructure systems remains largely siloed. Most research to date focuses on a specific problem in isolation, and limited review papers cover either a specific subset of AI methods [61] [62], or a specific infrastructure sector [63]. There is therefore a need to explore the use of AI in infrastructure systems through a cross-sectoral lens. This allows insights and lessons from certain sectors to inform how AI is used in others, as well as ensuring that the potential of

AI can be maximised at the intersections between sectors. By leveraging AI's capabilities, infrastructure systems can enhance their resilience, reliability, and sustainability, ultimately providing improved services to meet the needs of growing populations in the face of growing system complexity.

1.5 RELEVANCE OF SELF-HEALING IN THE WATER SECTOR

The water sector is concerned with the supply, treatment and distribution of water and wastewater. This is a sector facing considerable challenges, with increasing water scarcity and growing population and urbanisation levels putting pressure on both new and aging water systems [64].

In the UK, piped water became available to the vast majority of the population in the late 18th century. By the early 20th century most people had access to both piped water supplies and sanitation. These services were managed by a huge number of individual bodies (by 1945 there were more than 1,000 bodies involved in water supply and around 1,400 bodies responsible for sewage). Following the Second World War, there was significant consolidation of water services, ending with the establishment of ten regional water authorities for England and Wales in The Water Act of 1973 [65]. The regional authorities were later privatised in 1989, and remain privately operated today. The economic regulator for the water sector in England and Wales is The Water Services Regulation Authority (Ofwat).

A key issue facing the water sector today is the need to replace or upgrade aging infrastructure. While water companies do not publish data on pipe ages, and the pipe age for as much as 60% of the water network in England and Wales is unknown [66], it is recognised that the water infrastructure in the UK is aging significantly [67]. The costs involved in replacing or upgrading water systems, with massive underground pipe networks and often unreliable records, are massive. In England and Wales, the pipe replacement/renewal rate per annum sits at around the 0.05% of the network [68], while the equivalent average in Europe is 0.5% [69].

The water sector in England and Wales is facing huge pressure from the public to act on high leakage rates. While rates vary across England and Wales, with Thames Water (the company responsible for managing water in London and areas of South East England) the worst performing water company in the sector [70], it is estimated that 21% of total water supplied by the industry is lost as leakage [71]. There is significant backlash to spending on new infrastructure projects in the water sector while leakage remains so high. Leakage reduction also represents an area with great potential for improving sector efficiency, and reducing leakage is therefore a priority for Ofwat.

Improving efficiency also represents an opportunity for the water sector to reduce its energy use in water treatment and distribution. The water sector in England and Wales has a goal of achieving net zero by 2030, which will require improved efficiency as well as changes in demand behaviour [72]. While the water sector suffers from a poor public image, consumers are less likely to engage with demand-side behavioural change initiatives, perceiving the suppliers as not pulling their weight when it comes to improving the energy efficiency of the sector.

Many of these challenges facing the water sector can be addressed more effectively when considering water systems in a holistic manner. As complex and highly interconnected networks, water systems could benefit greatly from the adoption of a self-healing perspective. This includes both a systems-based approach and the integration of a proactive component to the management of water networks [73].

Self-healing systems can enable proactive monitoring and early detection of deteriorating infrastructure by leveraging near-real-time data and intelligent algorithms (often with machine learning). In systems such as water distribution systems, where failures such as leakages can be widespread and the replacement rate of the network is so low, there is a significant complexity in deciding which components or regions of the network to prioritise in order to make the necessary upgrades to the system in the most effective way. Self-healing systems can take on the challenge of identifying key areas for intervention and can automatically initiate repair or maintenance scheduling, minimising factors such as water loss and making the best use of available resources. This proactive approach can also incorporate early warning systems for potential water quality issues, such as contamination or chemical imbalances. Through continuous monitoring and analysis of water quality parameters, the system can detect anomalies and trigger alerts that can enable prompt action to mitigate risks and protect public health.

Self-healing systems can also optimise energy consumption in water treatment and distribution processes by employing methods such as machine learning tools to regulate pump operations, pressure management, and water flow control. These systems can dynamically adjust parameters based on incoming data, optimising system efficiency. Self-healing systems can also identify and rectify inefficiencies or malfunctions promptly, contributing to overall energy savings in the sector.

By demonstrating the proactive approaches enabled by self-healing, water companies can enhance consumer confidence in the sector. Improving performance on issues such as leakage, energy use, and sewage disposal, will rebuild public trust in water companies. Additionally, self-healing approaches should see a larger percentage of issues in the network identified by water companies themselves, rather than reported by consumers – leakage is an example of this. This not only improves system efficiency but demonstrates that improvement in practice.

The water sector is a good fit for a self-healing system approach due to its critical importance to society, the complexity of water distribution networks, and the potential for significant resource and cost savings. The implementation of self-healing systems within the water sector in England and Wales has the potential to address challenges related to increased demand, aging infrastructure, and growing environmental concerns. By leveraging advanced technologies, data-driven decision-making, and automated responses, self-healing systems can generate valuable insights into water usage patterns, infrastructure performance, and system vulnerabilities, and rapidly create a response to best act upon this insight. In adopting self-healing technologies, water companies can enhance operational efficiency, resilience, and sustainability, ultimately benefiting both the providers and consumers of water services.

1.6 RESEARCH QUESTIONS

The above sections outline the need to explore a self-healing approach for infrastructure system management, as well as the potential of AI to enhance self-healing capabilities. Therefore, this thesis seeks to address the following research questions;

- How can self-healing approaches, inspired by complex software-based systems, be adapted and applied to infrastructure systems?
- What are the key components and processes necessary for the implementation of a self-healing framework in infrastructure systems?
- How can AI techniques enable the processes of self-healing and be utilised within a self-healing framework for infrastructure systems?
- Which cross-cutting purposes can AI be applied to in infrastructure systems?
- What knowledge on AI application and methods could be transferred across infrastructure sectors?
- How would a self-healing framework be implemented in a case study scenario?

1.7 THESIS STRUCTURE

This thesis seeks to explore the overlapping fields of self-healing and AI, within the context of infrastructure system management. This thesis is comprised of six chapters, including this introduction (chapter one), which identifies the key research questions to be addressed in this study, introduces the self-healing approach, and explores the wider context of this research. This is followed by a literature review (chapter two) which details how both AI and self-healing have been applied to infrastructure systems. Regarding self-healing, there is a specific focus on the water sector, in anticipation of a water sector case study. Chapter three covers methodology, providing details of the methods used to conduct the literature reviews and describing how the dataset used for the case study is pre-processed in preparation for training the frameworks. This is followed by chapter four, focusing on the case study of a self-healing approach to leakage management. This chapter introduces the case study and presents the dataset used, before covering the development of frameworks to address the self-healing processes of anticipation, detection, and restoration of leakage in water distribution systems. The frameworks are then validated using a dataset provided by a large UK water company, and the results are presented. Chapter five presents a discussion, first presenting and exploring the comprehensive self-healing framework that has been developed and iterated throughout this research. The results of the case study are also discussed, as well as their implications for both academia and industry. This section also considers the limitations of the research and the considerations necessary for implementation of this research in a real-world setting and suggests possible areas for future research. Finally, the conclusion (chapter six) reflects upon the research and presents the contributions of this study.

2. SYSTEMATIC LITERATURE REVIEW

2.1 SELF-HEALING IN THE WATER SECTOR

2.1.1 LITERATURE SEARCH STRATEGY

2.1.1.1 Introduction

This section details the process of conducting a systemic literature review on the topic of self-healing in the water sector. As self-healing-specific terminology has not yet seen widespread uptake in this sector, the search strategy must consider how existing terminology and processes could contribute to a self-healing approach. The original search was conducted in 2020, but an additional search was performed in 2023 to ensure the review is up to date with any recent developments. The search uses the Scopus database. The findings of this literature review are presented in sections 2.1 and 2.2. The detailed search strategy and exclusion criteria are detailed in the following subsections.

2.1.1.2 Primary search terms

A systematic literature review is conducted to assess the state of self-healing within the water industry. With limited adoption of self-healing terminology in the water sector, it is decided that returning to the field of computational systems, where self-healing research originates, would provide a greater range of initial search terms. Papers describing the origins, principles, and development of self-healing systems are therefore used to create a broad list of terms linked to the concept of self-healing [49] [13] [14]. These are listed in Table 1

TABLE 1: SELF-HEALING SEARCH TERMS

Self heal*	Survivable	Self routing	Self recover*
Self protect*	Self repair	Self stabili*	Self adapt*
Self configur*	Self reconfigur*	Self optimi*	Artificial immune system

Key terms in the fields of water and wastewater, listed in Table 2, must also be included to ensure that search results address the appropriate sector. To ensure a manageable, yet relevant, list of papers, it is decided that, due to the broad nature of the water sector search terms, at least one of these terms must be present in the title of a paper. However, with self-healing terms still finding traction in the water sector, the presence of any one of the self-healing terms in either the title or keyword list is sufficient for inclusion.

TABLE 2: WATER SECTOR SEARCH TERMS

Water	Sewage	Irrigation

2.1.1.3 Secondary search strategy

Secondary targeted searches are conducted to ensure terminology specific to certain processes is included, yielding additional papers on autonomous decision support and system restoration.

Of the papers returned by the primary search, some of those most relevant to self-healing focus on DSS. While DSS are not inherently self-healing, the two types of system share several core principles. For example, both require an awareness of system state and thresholds to be set for any given interventions. While fully-developed instances of self-healing systems remain uncommon in the water sector, there is a more substantial body of research on DSS, which can overlap significantly with self-healing criteria. In order to understand the extent to which DSS have been applied to self-healing in the water sector, as well as the elements of self-healing that are most prevalent in this field, a second search was undertaken on the topic of DSS as applied to self-healing in water systems. As the focus of this search is on a specific method, the phrase ‘decision support’ has to appear in either the title, abstract, or keyword list, in addition to both a sector-specific term and a self-healing term. It is decided that a self-healing term must also be included to account for the varying degrees of autonomy in DSS. Any term beginning with ‘self’ is included, due to the lack of consensus in self-healing terminology within the water sector. It is noted that initial results feature many papers that are on a unit scale, rather than at system level, and so additional terms are added to ensure proposed solutions are addressing a network. **Error! Reference source not found.** shows the search string used to find papers in this secondary search.

FIGURE 6: SECONDARY SEARCH STRING FOR DECISION SUPPORT TOOLS

TITLE-ABS-KEY (("decision-support" OR " decision support") AND ("water" OR “sewage” OR “irrigation”) AND ("system" OR "network") AND ("self-*" OR "self *")

2.1.1.4 Mapping strategy

After searches on both self-healing generally, and DSS specifically, are conducted, the findings are mapped onto the key processes of self-healing systems. It is discovered that, while maintenance of system health and detection of system failure are addressed in the literature, there is an absence of work on the process of system restoration. To establish whether this is due to a genuine research gap or whether the terminology in the water sector for this process is not covered by the initial self-healing terms selected, a final search is undertaken. This search removes the need for any self-healing term but requires the presence of a variant of the word ‘restore’, as well as a water sector term. As in the previous search, the inclusion of system-wide terms is warranted due to a large number of results at unit level.

FIGURE 7: ADDITIONAL SEARCH STRING FOR RESTORATION PROCESSES

TITLE ("restor*" AND ("water" OR “sewage” OR “irrigation) AND ("network" OR "system"))

2.1.1.5 Inclusion criteria

The results of each search are screened for relevancy. The following criteria are applied to establish the final list of papers reviewed in this study.

1) A full text version of the article is available at the time of search.

2) The article addresses infrastructure at the system/network level, rather than household/unit level.

3) As self-healing is concerned with the health of existing systems, articles focussing on the design of entirely new infrastructure are not within scope. Similarly, articles proposing optimisation techniques are not included unless healthy and failed network states are defined, as this is necessary for the processes involved in self-healing to occur.

4) The article must address self-healing, or a process within the framework of self-healing. This must involve at least one of the following within the system; detection, preventative action, reactive action.

5) Where the article does not propose any interventions (actions) to the system but focusses on monitoring or detecting the state of a network, a 'healthy' threshold must be defined or demonstrated through a use case or case study. This threshold must either specify when the system has entered an abnormal or failed state, or establish a point at which interventions are required.

2.1.2 Findings – Self-healing in water

Through the lens of self-healing processes, the current state of system management in water infrastructure is examined, to establish the extent to which current approaches align with a self-healing methodology. A systematic review of self-healing in the water sector is conducted. With self-healing terminology not in widespread use in the water sector, and few examples of systems-based approaches, there must be a method for aligning the body of research in this sector with self-healing processes. Initially, based on literature covering a range of infrastructure systems, the self-healing processes are divided into cycles, with a cycle representing the process of remaining at or deviating from and then returning to a healthy state (this is discussed further in section 5, see Figure 1). However, it is instead found that the areas covered by the reviewed literature on water systems better aligns with the processes of detection, preventative action, and reactive action, which are shown in Figure 1. Each paper identified in the search is thus assessed and classified according to which of the three processes of self-healing – detection, preventative action, and reactive action – are addressed by the paper's proposed approach to system management. It is immediately evident that there are very few examples of complete self-healing systems. Instead, most research is focused on tackling issues that sit within a sub-section of a larger system. While limited research spans all three processes, each component of self-healing is represented within the full pool of papers. The dominant terminology found for each process, as well as in papers covering multiple processes, is presented in Figure 8, along with a selection of the techniques and algorithms employed.

FIGURE 8: TERMINOLOGY AND METHODS FOUND IN REVIEW OF SELF-HEALING IN WATER INFRASTRUCTURE.

Additionally, an analysis of the most commonly-used keywords found across the body of work shows high levels of connectivity, with each word linked to many others in the mapping. This demonstrates that the complex and interconnected nature of water systems is represented to an extent in the established body of research. While most individual research papers may align to only one or two of the three self-healing processes of preventative action, detection, and restorative action, it is seen that the components of water systems and the methods used to manage these components and their wider systems show significant connectivity. This demonstrates the suitability of a systems-based approach for the management of water systems; while often siloed in research, these systems are highly interconnected in practice. This mapping is shown in Figure 9.

'Decision support systems' appear as a highly used keyword, indicating that research in this area is acknowledging that the complexity of the systems and subsystems in the water sector presents a significant challenge for operators, and that computational support is required to achieve improved system management. It can also be suggested that the high number of links from terms such as 'artificial intelligence' show the widespread potential of this technology in the water sector.

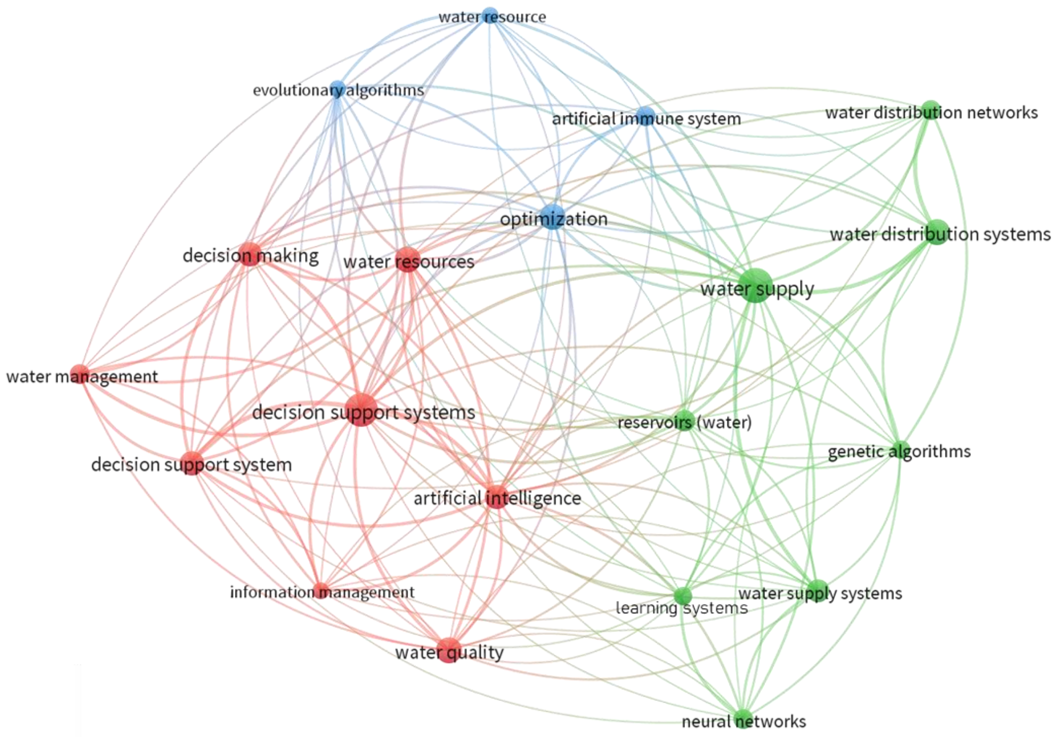


FIGURE 9: MAPPING OF THE 20 MOST FREQUENTLY-USED KEYWORDS, DONE USING VOSVIEWER SOFTWARE.

2.1.2.1 Detection techniques in literature

With self-awareness such a crucial element of self-healing, it is promising that detection techniques have been proposed for a large range of applications, including water quality [74], pipe leakage [75], irrigation [76], and reservoir monitoring [77]. The position of water infrastructure systems within larger environmental systems means that they are often affected by various environmental factors, such as rainfall, river flow, and groundwater levels, that are challenging to accurately monitor at scale. Integration of forecasting tools into models allows these variables to be considered, whilst also providing opportunities for failure anticipation [50] [78]. Forecasting of failure can also be facilitated by data from either hydrological forecasts or real-time sensors, with models able to predict the likelihood of failure events such as ice-jam or dry-up in river channels [78], allowing preventative interventions to be introduced. Another form of forecasting, damage forecasting, has been utilised in restorative approaches for networks where failure locations can be numerous and difficult to locate, such as water supply systems following an earthquake. A hydraulic analysis can instead take known information regarding the network and disruption, such as pipe properties and earthquake intensity respectively, to forecast damage within the system, allowing prioritised repair schedules to be developed [79] [80] [81].

For largely closed systems, such as water treatment plants, or those where data is required from specific sites, such as reservoirs, sensor-based approaches to detection are generally preferred. It is important to note that, in order to facilitate restorative interventions, a self-healing system must not only detect its present state, but define a threshold at which that state is deemed unhealthy. Approaches to this have included defining an unacceptable deviation from previous measurements [82] or training data [39], and using limits defined in standards or legislation.

2.1.2.2 Detection with preventative action techniques in literature

Effective monitoring can detect minor fluctuations and enable early interventions to prevent a degradation in service. The most popular research direction at the overlap of detection and preventative action is the design of controllers. Many of these are fuzzy self-adaptive controllers, providing greater system autonomy even in fluctuating or uncertain conditions. As might be expected, these are particularly prevalent in multi-variable water/wastewater treatment systems [83] [84] [85] [86], although controllers can also facilitate the operation of canals [87] [88] and water supply systems [89]. Preventative action interventions in the absence of detection technologies were found to be relatively rare, again underscoring the importance of system awareness in self-healing. The few papers that attempt this have centred on resource allocation in water management, seeking to optimise variables such as cost and reliability and reduce flood risk in a range of potential resource distribution scenarios [90]. With multiple variables to consider, multi-objective evolutionary algorithms have proven popular for tackling water resource allocation problems [91] [92].

2.1.2.3 Detection with reactive action techniques in literature

It is at the intersection of reactive interventions and detection methods that DSS sit. Whilst human operators are largely still necessary, the actions of operators are guided by insights generated by the system itself. Triggering these actions can be as straightforward as the sending of automated alerts in response to the detected variable crossing beyond a failure threshold [38]. DSS operating with high degrees of automation have been applied to pathogen monitoring in drinking water [74], siphon operation for flood mitigation in wetlands and shallow ponds [93], and river pollution control [94].

2.1.2.4 Preventative and reactive action techniques in literature

A notable finding is that preventative and reactive actions are rarely addressed within the same paper. Instead, research is focussed either on preventing failures that can be anticipated, or on restoring the system after unavoidable failure. Interestingly, both have been approached from a resource allocation perspective, with the former allocating water across rivers and reservoirs, and the latter allocating emergency response resources such as repair crews. It is evident that it is in the area of reactive interventions that water systems still rely on a significant degree of human involvement. With the complexity involved in fixing water infrastructure, particularly underground services, it is likely that many systems in this sector will need to be assisted-healing systems until advances in enabling technologies can be made. Existing research in this area, however, takes decisions on how to prioritise repairs out of human hands. In disaster response scenarios, reactive approaches vary from a dynamic cost-benefit method [81] to prioritisation of restoring water supplies to emergency facilities such as hospitals and fire stations [95].

2.1.2.5 Self-healing techniques in literature

Only two papers are identified that include all the core components of self-healing systems, with detective capabilities in addition to both preventative and restorative interventions. The first tackles irrigation, where the difference between damaged and broken states is typically down to the degree of severity. Recent developments in smart irrigation systems have enabled extensive system monitoring through the Internet of Things. The authors adopt a constraint-based approach, defining the properties that a solution is required to have, rather than a set of specific instructions, and delegate the decision making to a solver [76]. The second is an ambitious attempt at real-time regulation of resources within the Yellow River basin. Access to real-time information on user requirements and channel flow allows for dynamic adjustments in water diversion and reservoir release. The paper is somewhat lacking in detail regarding how decisions are made during periods where river discharge is unable to meet the needs of all users, but it demonstrates well how a systemwide approach can be applied beyond smaller water infrastructure networks to the more challenging systems of river basins, which themselves sit within wider and more complex environmental systems [78].

2.1.3 Findings - Data for self-healing in the water sector

2.1.3.1 Introduction

A crucial element of self-healing systems is their ability to detect their present state and distinguish between healthy and failed states. As such, access to up-to-date sensing data regarding the properties and key variables within an infrastructure network very much underpins the effectiveness of a self-healing system. It is found, however, that many of the techniques considered in this review are yet to be demonstrated on data from a live network. This may speak to the relative newness of system-based approaches such as self-healing in the water sector. Several alternatives, including historical and benchmark data, are used instead to establish the performance of proposed techniques. While this is often sufficient to demonstrate how active interventions would utilise data to heal the system, some methods may not address potential challenges in data collection and accuracy.

2.1.3.2 Inputs absent

In several instances, it is not evident how inputs would be measured or from which database they would be imported. Where access to the required information is assumed, it is often the case that the article is focussed on developing a system architecture, such as a decision support framework, rather than on integrating the required knowledge base. Such techniques can depend on the user being able to input known data themselves [94].

While it is recognised that there is often value in integrating weather or rainfall forecasting into water system methods [96], it is typically expected that this information is supplied by external agencies, rather than generated by the proposed technique. It is not uncommon for the source of forecasting data to remain unspecified, particularly in the absence of a real-world case study [93].

2.1.3.3 Benchmark data

For more established scenarios, such as wastewater treatment processes, benchmark models have been developed in order to evaluate proposed interventions. Benchmarks set particular parameter values, define average and threshold values, and specify performance assessment metrics. An established benchmark utilised by reviewed articles is Benchmark Simulation Model no. 1 (BSM1), a nonlinear process benchmark for the wastewater treatment process developed by the International Water Association and composed of a five-part activated sludge reactor [97]. BSM1 is used to assess the performance of model predictive control for self-optimisation of wastewater treatment plants, modelling disturbances caused by various weather events [98] [85].

2.1.3.4 Chosen values

In some cases, it can be necessary to make assumptions about the values of particular variables. It may be that sufficient or reliable data is unavailable, or that arbitrary values are deliberately chosen to illustrate the generality of the proposed technique. Chosen values are often selected for only a small number of relevant variables, with other variables relying on benchmark, historical, or modelled data. In many cases, chosen values are informed by expert knowledge of operating conditions, such as in wastewater treatment processes [99].

Perhaps the most common example of the use of chosen values in the literature reviewed is in restoration of water networks. Again, knowledge from industry experts can be of value here, with one study on repair scheduling assuming 13 pipe breakages to be dealt with by three repair crews, based on maximum break rates and minimum crew levels provided by the company managing the case study area [100]. When more arbitrary values are used, it is often for the purpose of comparison of either different models or of different scenarios. For example, a study on post-earthquake repair selects reasonable if unexplained values for pipe properties, earthquake intensity, source and consumer head, and then demonstrates the proposed framework on models of a small and medium network, ensuring that these parameters are kept consistent across both models [101]. While this may not be representative of a real-life network, it allows for a simple comparison of the performance of the framework across the two scenarios.

2.1.3.5 Simulated data

Where input data is required from known yet rare phenomena, this data can be simulated using pre-existing models or simulators. Restoration of water networks again offers a useful example of this, particularly when considering an extreme event such as an earthquake. As earthquakes are rare events, data on pipe breakages and repairs in their aftermath can be very limited. Rather than relying on limited, and perhaps very context-specific, historical data, research can use a model to predict how, under earthquake conditions, breakages might occur in a given network [79]. Once these breakages are mapped onto the network, methods for optimising repair can then be explored. As any network, real or simulated, could be input into the initial earthquake breakage model, some of the context-specific limitations of using historical data can be avoided. For example, countries with decentralised or low-tech water systems are less likely than those with centrally-managed, higher-tech systems to have complete and comprehensive records of breakages and repairs in the event of an extreme earthquake. Similarly, repair priorities may differ across nations and regions [81]. Thus, using predictive models for breakages can allow a range of contexts to be explored.

It is worth noting that it is not only in cases of extreme events that simulation data can be used. Established simulators such as EPANET, a widely-known water distribution network simulator, are often favoured by researchers as a base on which to develop and validate their methods [102] [103]. Using a simulator can get around the challenge of securing access to sufficient data, and widely-used simulators have the benefit of being trusted within the research community. Furthermore, if a simulator is sufficiently adopted as the standard within a given field, it allows for easy comparison of proposed methods.

2.1.3.6 Historical data

Historical data from a real-world system can be a valuable option for validating model performance. Indeed, many traditional and machine learning-based methods require sufficient quantities of training data that is best provided through historical datasets of the same system being modelled. That being said, it is important, when using historical data, to ensure that the sample provided is representative. For infrastructure systems, shifts in population levels and distribution, advances in technology and efficiency, and changing consumer demand behaviour may render some historical datasets too different from current patterns to be useful for model training. Similarly, extreme events may result in periods of unusual data, and this can be either beneficial or detrimental to model training and validation depending on whether this data is flagged as unusual and how this data is used. If a model is to be able to capture or predict behaviour of infrastructure systems during a rare extreme event, such as an earthquake, training data that contains examples of system behaviour during a previous event can be very rare and thus very valuable if identified as such. However, some models may want to exclude any examples of atypical system behaviour, for example those seeking to forecast usual daily water usage may want to remove any training data with large bursts or firefighting events. This again relies upon the unusual data being identified in the dataset. If extreme events are not picked up and flagged as such, this can present difficulties in training a model. While short extreme events may have a limited impact on training, extended periods of unusual behaviour can be more damaging. For example, consumer demand of both energy and water during a weekday has historically followed a regular pattern, with peaks right before and after typical working hours. However, during the recent COVID-19 pandemic, which saw widespread working from home for a large portion of the population, these long-established patterns changed to reflect the shift from out-of-home to in-home working. A model trained on data gathered during a COVID-19 lockdown would therefore be expected to produce different results than a model training on pre-2020 energy or water demand values. It is therefore important to recognise extended periods of change in any historical data and assess which sections of the dataset, if any, can be said to best reflect to current live system.

There are numerous examples of utilising historical data in the literature covered by this review. One study, which uses a co-evolutionary artificial immune system model to derive water-supply reservoir operating rules based on reservoir inflow and water demand data from 1956 to 2000, demonstrates the importance of considering long-term unusual events in historical data. An analysis of initial classification results found that samples corresponding to a drought period were more frequently misclassified. By adding further examples into the training data that had been identified by the rules that had misclassified the drought data, identification rates improved across the board but particularly for drought years [104]. Hence, the authors recommend continuously adding 'abnormal' samples to the training dataset to better enable the model to deal with abnormal operation environments such as drought.

Using datasets spanning several decades is not unusual in the field of water resource management, particular for reservoir data. One study on resource allocation in Iraq's Diyala river basin uses a monthly dataset of reservoir releases from 1981 to 2012 [91], while another study in the Dongjiang river basins of South China uses inflow data from 1956 to 2005 [105]. Finally, an early-warning system for reservoir release is demonstrated on seven years of data recorded by operators of the Timah Tasoh reservoir in Malaysia from 1998 to 2005 [77]. The use of such volumes of historical data is perhaps in part due to reservoir data being largely dependent on weather patterns, which are often heavily seasonal and thus similar patterns would be expected year-on-year. The availability of data stretching so far back is likely also a factor. However, the growing impacts of climate change should be considered when assessing whether historical climate data can be representative of modern patterns, and a greater frequency of extreme events such as droughts should be expected. The multi-objective immune algorithm used in the Dongjiang study also makes use of population and water demand data from 2010, as well as economic data from the 2000s [105]. This highlights another factor that should be considered when using historical data, which is whether datasets for different variables need to cover the same time period. While this may be the ideal scenario, factors such as availability of data and maturity of technology may limit some data. Utilising data from different periods may therefore help develop a more comprehensive model, but explicit consideration should be given to whether the datasets are similarly representative.

2.1.3.7 Testbed setup

An alternative to data from a live real-world system can be data from a testbed setup. Such setups can be run as a live system and thus do accurately represent some of the challenges of dealing with incoming data in real-time, such as having the necessary computing power and dealing with sensor errors. Testbed setups can also allow for the trialling of new technologies for which widespread or rapid rollout may currently be unfeasible. An example of this would be acoustic monitoring in water distribution systems [106]. Trials using testbed setups can better establish the potential of such technologies and provide insight into how to most effectively implement the technology at a larger scale. Limitations of testbed setups are of course that the data may not be fully representative of the real-world system. For systems such as water distribution systems, assumptions have to be made about demand behaviour and about modes of failure. Testbed setups also tend to be significantly smaller in size than their real-world counterparts, consisting of fewer components and representing small geographic area.

2.1.3.8 Live data

While access to sensor data from live real-world systems can be very challenging to acquire, this data is incredibly valuable is assessing the effectiveness of proposed methods for managing these systems. Many infrastructure owners and operators are hesitant to share such data, often citing data security and privacy concerns, as many elements of critical infrastructure systems are concerned with the safety and privacy of consumers. These issues can extend to historical data as well as live sensor data. Data security concerns can perhaps be overstated, however, as a reason for limiting access to infrastructure data. Having data architecture in place to systematically record, store, and share data streams can be an additional limitation, as well as concerns regarding public perception of infrastructure performance that may arise from open data. Typically, access to live data is secured through an agreement with the infrastructure provider that guarantees a level of protection regarding what can be publicly shared.

One study, which analysed flow data for anomaly detection across a live water network, had access to regular flow data for over 140 district metered areas (DMAs) for one year. This case study produced almost 200 alerts, 36% of which were found to correspond with bursts. Other alerts were attributed to abnormal flow demand, data issues, or 'ghost' events [38]. This illustrates how using live data can expose potential issues with proposed techniques, with the identification of a reliable failure threshold being perhaps one of the biggest challenges.

The historical data used to demonstrate proposed techniques can be from a system with the capacity to provide real-time data. In such instances, historical records, rather than a live data sample, may have been chosen for reasons of access, simplicity, or to ensure a representative spread of data was selected. These methods should, therefore, be able to operate with real-time data with relatively minimal technical changes. However, it is important to recognise that importing real-time data can pose additional challenges, including data completeness, reliability, and security issues, that may not be addressed in research that uses historical data to verify proposed techniques. In one example, a leakage detection methodology designed to operate on a live system is trained on three years of historical data [75]. Recognising that a significant portion of this data contained missing or erroneous values, it is necessary to pre-process this data to provide complete and continuous data to the proposed model. As live data would likely have the same, if not more, issues, any potential impact of this pre-processing on the feasibility of model implementation should be considered.

2.2 ARTIFICIAL INTELLIGENCE METHODS AND THEIR APPLICATION IN INFRASTRUCTURE SYSTEMS

2.2.1 LITERATURE SEARCH STRATEGY

2.2.1.1 Introduction

This section details the process of conducting a literature review on the topic of AI in infrastructure systems. This review adopts a systematic literature review approach in combination with a snowballing literature review method proposed by Wohlin [107], which is applied to review papers or highly significant papers. Wohlin's systematic literature review with snowballing is chosen over a sole database search-based review due to the interdisciplinary nature of the research area, which spans a range of sectors, making it challenging to formulate comprehensive search strings. This helps to overcome the additional difficulty of creating precise searches, with the risk of yielding many irrelevant or redundant papers [108]. This search was initially conducted in 2021 but updated in 2023 to address any new research in this field. The search uses the Scopus database.

The scope of this review is very broad in it's aim. The field of AI is rapidly developing and research in this area is growing in both quantity and complexity. The exploding interest in this field was evident from the 2023 update of this review, which saw an exponential increase in the number of papers meeting search criteria. It is therefore worth clarifying the goals and limitations of this review.

This review brings to light the most common applications to which AI has been applied in infrastructure systems, and the most common methods that have been used. The coverage of methods refrains from being too specific regarding the many subtypes of machine learning algorithms, sticking largely to broader categories of algorithm. This is a reflection of the focus on infrastructure applications of AI, rather than the detail of the AI methods themselves. By reviewing this literature from multiple perspectives, it is hoped that these insights will be of value to researchers concerned with specific infrastructure sectors as well as those looking at cross-sectoral applications of AI in infrastructure. The findings provide a starting point, considering the strengths of proposed solutions as well as the research gaps in existing literature, from which researchers can delve deeper into their specific interests. With research in this field continuing to grow and evolve, it is expected that the landscape of AI in infrastructure will change dramatically in the coming years. This review could therefore act as a reference from which to compare the state of the art in this field in the future.

2.2.1.2 Primary search terms

The systematic selection of a tentative starting set of papers is undertaken. Search terms are divided into two categories: AI terms and infrastructure terms. AI terms cover the range of subtopics within the field (Table 3). Infrastructure terms vary across systems, so these terms can be subdivided into the infrastructure systems of transportation, energy, water/wastewater and telecommunications (Table 4). These terms are used for a primary search, the results of which informs the purposes chosen for discussion in section 2.2.3. To ensure the key papers are covered for each purpose, a range of more general terms pertaining to purpose are applied to multiple infrastructure sectors as part of a secondary search (Table 5). The reviewed papers are categorised by AI method, infrastructure sector (or sectors), and purpose.

This review was originally written mid-2021 and was updated in 2023 to reflect recent advancements in what is a rapidly advancing field. As such, the number of papers returned by an updated search of the original search terms show exponential growth in publications over the interim years. In order to ensure both that this review is sufficiently concise and that the most relevant latest research in AI is included, the search strategy is refined for this update. First, to include any significant new work covering purposes that are already explored, targeted searches were carried out for each of the purpose terms in Table 5. To be included in this search, papers must include at least one AI term from Table 3, an infrastructure term from Table 4, and the selected purpose term from Table 5. This process is repeated for each purpose term. Then, to make sure that any new or emerging purposes are captured in the update, a search is carried out using only the AI and infrastructure terms in Table 3 and Table 4, with results sorted by most citations. Papers that are already picked up by the purpose-specific searches are removed, and then the most cited of recent work is subject to a title and, if necessary, abstract screening. If the paper is found to be relevant to this review and represents a new purpose to which AI had been applied in infrastructure, it is selected for inclusion and the purpose section is updated to reflect the new application of AI in infrastructure.

TABLE 3 : AI TERMINOLOGY

Artificial Intelligence Terms	
Artificial Intelligence	Fuzzy Logic
Artificial Neural Network	Knowledge representation
Automated Reasoning	Machine Learning
Autonomous Robotics	Natural Language Processing
Computer Vision	Ontology
Convolutional Neural Network	Robotics
Deep Learning	Semantic Web
Expert System	

TABLE 4: SEARCH TERMINOLOGY FOR INFRASTRUCTURE SECTORS

Transportation	**Energy**	**Water and Wastewater**	**Telecommunications**
Transport	Energy	Water	Telecom
Rail	Smart grid	Wastewater	Data demand
Highway	Renewable	Sewage	Customer churn
Motorway	Wind	Water treatment	Smartphone
Road	Solar	Pollutant removal	Network design
Traffic	Nuclear	Irrigation	Network management
Vehicle	Oil	Water quality	Software Defined Network
Freight	Gas		Traffic routing
Shipping	Bioenergy		4G
Car	Hydropower		5G
Bus	Electricity		Passive Optical Network
Electric vehicle	Generation		Satellite
Accident forecasting			VANET
Navigation			

TABLE 5: PURPOSE TERMS FOR SECONDARY SEARCH

Infrastructure Purpose Terms	
Forecasting	Anomaly detection
Demand forecasting	Maintenance
Supply forecasting	Inspection
Price forecasting	Monitoring
Site selection	Quality
Security	Routing

2.2.1.3 Screening strategy

Initial searching combines each AI term with the sector-specific infrastructure terms. An expert in telecommunication systems, Dr Oughton of Oxford University, is consulted in order to ensure domain-specific terminology is included. Search strings combining multiple infrastructure sectors are also used, to find papers covering overlaps in infrastructure sectors such as the water-energy nexus. The results of this initial search inform the infrastructure purpose terminology selected. In an additional step, the purpose terms identified from the primary search results are then used in a secondary search, where they are combined with AI terms in order to account for key papers pertaining to specific applications. Results are subject to title screening to ensure relevance. Further exclusionary criteria are applied, removing those not papers written in English, those that fall outside of the scope of infrastructure systems, or those that explore algorithms outside of machine learning models. Papers are collated, and those concerned with the same infrastructure and purpose are assessed, with factors considered including date of publication, number of citations and number of comparative models studied. Papers are also labelled to identify those that could be described as review papers. Review papers and the most relevant and comprehensive of non-review papers are then subject to snowballing. Title screening of results establishes relevance, and a secondary abstract screening is sufficient to apply exclusion criteria in the majority of cases. Where this is not the case, the full paper is assessed prior to inclusion.

2.2.1.4 Review statistics

There are a total of 349 papers selected for this review. The papers included in this review are published between 1991 and 2023. 86% of papers are published in the year 2014 or later, with the publishing years of all papers shown in Figure 10. The huge growth of AI in recent years is evident from Figure 10, with this field expected only to grow in the coming years based on current trends.

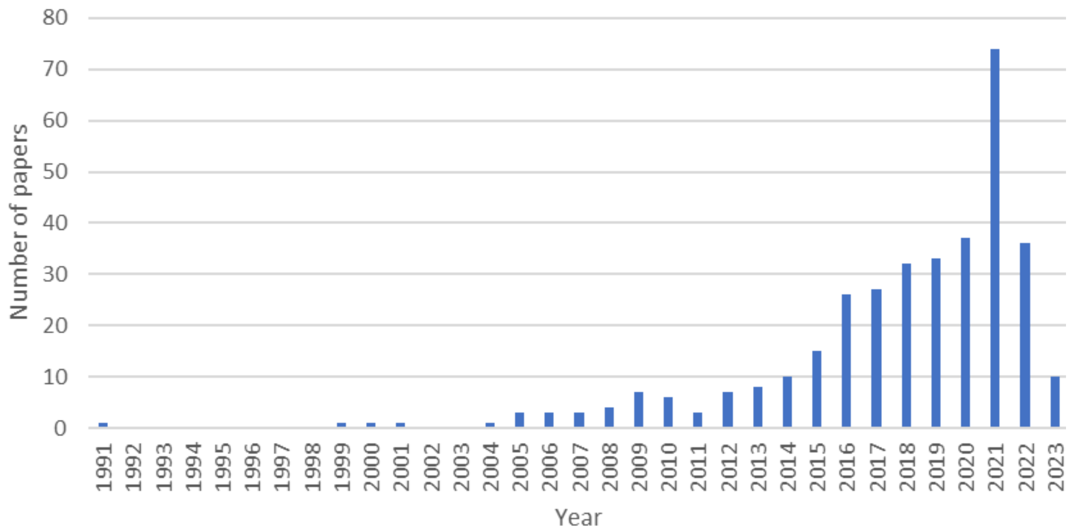


FIGURE 10: PUBLISHING YEARS OF PAPERS INCLUDED IN REVIEW OF AI IN INFRASTRUCTURE SYSTEMS

2.2.2 INTRODUCTION TO FINDINGS

AI methods enable machines to learn and infer from large volumes of data [42]. As infrastructure systems become increasingly interconnected, complex and digitalised, AI will be crucial in providing and maintaining services that ever-increasing numbers of people depend upon every day [45]. However, as interest in AI continues to grow, research into its application to infrastructure systems remains largely siloed. Most papers focus on a specific problem in isolation, and the handful of review papers cover either a specific subset of AI methods [61] [62], or a specific infrastructure sector [63]. There is a need to consider the body of research into AI in infrastructure systems as a whole, looking at the most common and effective methods and the purposes to which they have been applied, which often span multiple infrastructure sectors. This review explores the current state of research on AI in infrastructure at the system level. The most widespread methods are first detailed, in order to provide context for the second subsection which investigates some of the more popular purposes to which AI has been applied across infrastructure systems.

2.2.3 Findings - AI methods

Alan Turing proposed his 'Turing test' to offer an operational definition of AI, stating that a truly intelligent system must be capable of matching human cognitive performance to an extent that a human interrogator cannot tell the difference between human and machine when interacting via a teletype system [109]. In a 'total' Turing test, perception and physical abilities are tested alongside cognitive functioning. Each of the following components represents a field of AI that help to attain one or more of the Turing test's goals:

- knowledge representation, to store data
- automated reasoning, to infer and make use of conclusions from the stored data
- machine learning, to identify patterns and modify behaviour
- computer vision, to perceive the environment
- robotics, to interact with the physical environment
- natural language processing, to communicate in human language

While these components can describe attributes of an ideal intelligent computer system, they can also be considered topics in the field of AI research, each concerned with techniques that contribute to an element of system intelligence.

There is significant overlap between fields, with automated reasoning inherently dependent on the knowledge base it reasons from, machine learning techniques – particularly convolutional neural networks – increasingly utilised in computer vision systems, and such vision systems often integrated into intelligent robots. Models which include both a reasoning and machine learning element, such as adaptive neuro-fuzzy inference systems (ANFIS), are also growing in use. The following section describes each field of AI and explores some common methods within each field. It should be noted that the methods described in this section are not a comprehensive review of all techniques but rather the most common methods found in the body of work reviewed, as to provide context for further discussion.

2.2.3.1 Knowledge Representation

Knowledge representation is concerned with building and structuring a knowledge base that captures information about the world in a way that allows it to be processed by computing systems. In the field of AI, it has been suggested that knowledge representation is fundamentally a computational surrogate for real-world entities, providing the capacity to determine consequences through thinking about the world, rather than taking action in it [110]. Knowledge representation tools include semantic networks, ontologies, frames and system architectures.

Semantic networks represent knowledge using a graphical structure of interconnected conceptional nodes and directional relationship arcs [111]. These are one of the most conceptually straightforward knowledge representation tools, so their intuitive structure has seen semantic nets applied to a range of infrastructure systems, including energy management [112] and the challenge of creating a large-scale sensor network architecture in the form of a 'web of things' [113]. Frames are derived from semantic networks, with nodes and 'relations' between nodes arranged in a series of levels to represent a stereotyped situation [114].

Ontologies capture and present formal terminology for entities in a given application domain, while employing a semantic approach to illustrate relationships between them, in order to simplify the challenge of generating meaningful information from raw data [115]. Such domain ontologies provide a controlled vocabulary of concepts, syntax and semantics that facilitate communication between user and machine [116]. Ontology-based approaches are used in a variety of infrastructure systems [115] [117] [118], and have been proposed as a tool for organising the sensor networks that play an important role in the 'Internet of Things' [119] [120].

A key purpose of explicitly representing knowledge is to be able to reason about that knowledge, allowing the system to draw conclusions and deduce new knowledge. As a result, most knowledge representation languages have an integrated reasoning or inference engine, demonstrating the close link between knowledge representation and automated reasoning [121].

2.2.3.2 Automated Reasoning

Automated reasoning is concerned with utilising system knowledge to make logical inferences from given premises. In the context of AI, this is often used to provide a decision-making framework that allows the system to independently work towards goals without human interaction. The efficiency of reasoning methods is therefore heavily dependent on the knowledge representation approach selected [122]. Expert systems combine a knowledge base and reasoning mechanism to emulate the decision process of a human expert. The reasoning process is typically performed by an inference engine, classifier, or rule interpreter, which applies predetermined logical rules to the knowledge base in order to determine new information [121].

While automated reasoning can utilise classical logic, which typically yields Boolean 'true' or 'false' outcomes, other techniques have attempted to account for the fact that human reasoning is often based on imprecise, partial, or qualitative data. Bayesian inference takes a probabilistic approach, updating probabilities based on observed data. This reasoning method underpins some machine learning techniques, including Bayesian network-based methods and Naïve Bayes classifiers. In infrastructure systems, examples of their application include flow prediction and anomaly detection [123] [124] [125].

Another reasoning system that seeks to incorporate the ambiguity of many real-world situations is fuzzy logic, which assigns a value between 0 and 1 to represent the extent to which inputs can be mapped to membership values [126]. It is possible for inputs to be assigned multiple memberships, although to varying degrees. Using this 'degree of membership' methodology, human subjectivity can be factored into the reasoning process. As an example, the wind speeds at a potential wind farm site could be classified as 'high speed' to a degree of 0.8, 'average speed' to a degree of 0.2. As membership functions can be designed to account for population variables, different assignments may be expected for different seasons or geographic regions – what is 'high' in the British summertime may be considered 'low' during typhoon season in Asia. Fuzzy logic is widely applied to site selection [127] [128] [129], and in a range of applications across renewable energy systems [61].

2.2.3.3 Machine Learning

Machine learning is the process by which machines, able to access the necessary knowledge, can modify and adapt their actions to learn independently how to solve problems [130]. Machine learning is a subset of AI, but there exist further subsets of machine learning, including deep learning, as shown in Figure 11. There are a large range of machine learning models, which generally utilise three widely recognised types of learning: supervised, unsupervised and reinforcement. Learning styles typically address how, and the extent to which, models are trained.

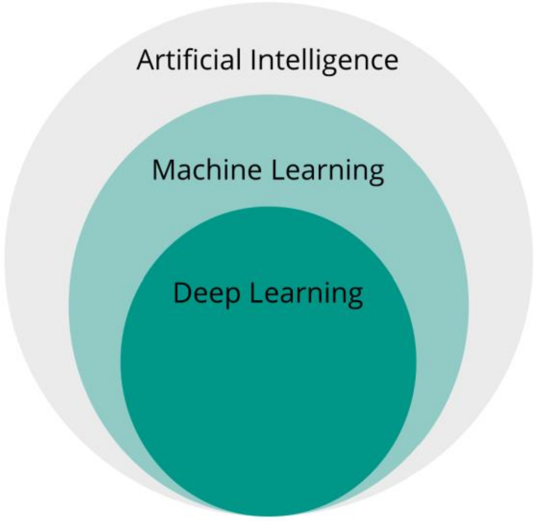


FIGURE 11: THE RELATIONSHIP BETWEEN AI, MACHINE LEARNING, AND DEEP LEARNING.

Learning Types

A. Supervised Learning

In this type of learning, the system is trained using a set of examples with the desired responses provided [131]. Given sufficient training, which can take hours, days, or longer, the system can generalise in order to map inputs to outputs for new data sets. This can also be described as learning from exemplars [130]. Supervised learning models may require retraining to account for changes in their inputs over time.

B. Unsupervised Learning

Unlike in supervised learning, in unsupervised learning, the correct outputs are not provided alongside inputs. Instead, an unsupervised learning agent has to rely on its own ability to identify the embedded structures or patterns in inputs, so that those with similarities can be categorised together [130] [131]. This approach to learning typically aims to discover analogous input groups, a process known as clustering, or to establish the distribution of data within the input space, a statistical approach known as density estimation [132].

C. Reinforcement Learning

In reinforcement learning, there are no pre-classified examples, but there is some form of long-term objective. An agent ‘experiments’ with a system, and receives rewards or punishments based on these interactions. The agent tries different possibilities, optimising its behaviour over numerous iterations in order to maximise rewards and minimise punishments [133]. While the agent is never explicitly given instructions as to how to achieve its goal, acting in ways that maximise the cumulative reward allows it to develop optimal behaviours, in as many iterations as needed [131]. In most cases, the longer a model is run, the more refined the solution will be.

Common Machine Learning Models

Although the specific details of a model’s architecture and algorithm vary for each individual case, there are a number of popular machine learning models that have established themselves as some of the best performing.

A. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are a popular type of machine learning model that simulate the mechanism of learning in the human brain, which contains networks of billions of nerve cells. In ANNs, a neuron is a computational unit consisting of ‘dendrite’ inputs scaled with ‘synaptic’ weights that affect the function computed at that unit, and an ‘activation’ internal state [134]. Neurons exist in a network, forming a directed, weighted graph that is typically arranged in layers. The learning process occurs by modifying the weights and thresholds of the network to achieve accurate results.

Although there are so many variations of ANNs in use today that it is impossible to cover all of them in detail, a few of the most popular model structures are outlined here. ANNs can be divided into two classes based on their general architecture: feed-forward and feedback networks. Feed-forward networks are non-recurrent networks comprised of inputs, hidden layers, and outputs, where signals can only travel in one direction. Examples include multilayer perceptrons (MLPs) and radial basis function (RBF) networks. Use cases in infrastructure research have seen MLP models employed to predict energy consumption [135] and for pollutant removal [136] in water networks. RBF networks have also been applied to water treatment [136].Conversely, feed-back networks permit signals to travel in either direction, owing to the inclusion of feed-back loops. In feed-back networks, also called recurrent neural networks (RNNs), neurons can be connected in any possible format, which can account for dependencies between neurons. Popular RNNs are echo state networks (ESNs), and long short-term memory (LSTM) networks. Interesting examples in infrastructure have seen ESNs applied to demand forecasting in water networks [137], while LSTM networks can be found in a range of forecasting applications. LSTM networks have been used to predict energy use [138], telecommunication traffic [139] and accident risk in transport networks [140], to give just a few examples.

Another type of ANN, convolutional neural networks (CNNs), have been widely used for image classification and object detection purposes. This particular application of AI can be described as computer vision and is covered separately.

B. Support Vector Machines (SVMs)

Support vector machines (SVMs) are popular machine learning models widely used in classification and regression tasks, although used most extensively for the former. When applied to regression tasks, SVMs may be described as support vector regression (SVR). SVMs work by mapping input vectors into a high dimensional feature space and finding an optimal hyperplane to classify the data. The dimension of the feature space is dependent on the number of input features [141]. The SVM algorithm seeks to maximise the margin between data points and hyperplane, which it does using a loss function. SVM-based approaches have been used in energy demand and price forecasting [142] [143], for routing in vehicular networks [144], and to assess and improve quality and security in telecommunication systems [145] [123] [146].

C. Decision Trees (DTs) and Random Forests (RFs)

Another technique that has been applied to both classification and regression tasks is decision trees (DTs). In DTs, inputs begin at a root node, where a specific attribute is tested, with the result dictating the branch down which the unit is sent. This process is repeated, with different tests at each node, until a terminal, or 'leaf', node is reached [147]. Regression trees, which are applied to continuous variables, obtain leaf node values from the mean response of regional observations. However, the leaf node values of classification trees, which deal with categoric variables, are the mode of regional observations.

Random forest (RF) models consist of large numbers of DTs operating as an ensemble. Building units using random feature selection results in low correlation between the trees, limiting the spreading of errors between them [148]. RFs have seen wider exploitation than DTs in infrastructure systems, where they have been applied to quality of experience prediction [149] and anomaly detection [150] in telecommunication networks, price prediction [151] and pollutant removal [136] [152] in water systems, and behaviour prediction in transport [153].

D. K-means Clustering

One of the most common unsupervised learning tools is k-means clustering, which assigns inputs to a cluster based on the distance from cluster centroids, in order to maximise similarities within groups [154]. In infrastructure, k-means has been used in telecommunication routing [155] and security [156], as well as for behavioural prediction in transportation modelling [153].

Deep Learning

Deep learning is a relatively new branch of machine learning, describing computational models composed of multiple processing layers that learn representations of data with multiple levels of abstraction [157]. While the first deep learning algorithms and architectures were developed in the 1960s and 1970s, massive advances in computer hardware are responsible for the deep learning revolution of the past ten years.

In practice, deep learning applies specifically to ANN models, although architectures can show significant variation. Deep ANNs are any that contain multiple hidden layers. Examples of deep neural networks include Deep Belief Networks (DBNs), autoencoders, LSTM and CNNs. The depth of these networks allows very complex functions to be learned. Models such as DBNs and autoencoders often include an unsupervised pre-training stage, which capture the main variations in inputs and can yield better generalisation [158].

Capable of handling problems with very large quantities of data, deep learning has proven to be very successful at tackling particularly complex problems, such as image classification, natural language processing, and speech recognition. However, deep learning is not without drawbacks. Large datasets, in addition to the increased computational complexity of deep ANNs, can result in longer training and run times, which are of particular concern for real-time applications.

2.2.3.4 Computer Vision

Computer vision is concerned with learning the relationships between observed image data and aspects of the world, such as the 3D structure or the object class, and exploits this knowledge to make new inferences from new image data [159]. Both biological and computational vision systems require several basic components: a radiation source, a camera, a sensor, a processing unit, and an actor. A complete computer vision system uses these to cover a range of processes from image construction to formulating a response to perceived actions [160].

Traditional methods in computer vision have utilised feature-based approaches such as scale invariant feature transform (SIFT), speeded up robust features (SURF), features from accelerated segment test (FAST), Hough transforms and geometric hashing, sometimes in combination with machine learning classifiers. While these tools still have a place in computer vision, the adoption of deep learning methods has transformed this field [161]. In recent works, deep learning often underpins the design of the processing unit in computer vision systems.

The most dominant tool used in the processing stage of computer vision systems is the CNN. CNNs are biologically inspired networks which are widely used for image recognition, classification, object detection and localisation [134]. Although developed in the 1980s, it was the development of graphics processing units in the 2000s that saw CNNs take off in popularity, by vastly reducing run times. CNN architecture is designed for grid-structured inputs with strong localised spatial dependencies. The convolutional layer utilises kernel elements, which are 3-dimensional structural units, to abstract an image to a feature map, in order to extract high-level features such as edges. Each layer of a CNN is 3-dimensional, with a spatial extent and a depth corresponding to the number of feature maps in that layer [162]. In infrastructure, CNNs have been applied to structural health monitoring [163], water quality assessment [164], and autonomous vehicles [165].

2.2.3.5 Robotics

Robotics is a unique branch of AI that operates in the real-world, rather than computer-simulated worlds. The discipline of robotics is concerned with the design, construction, and use of machines to perform traditionally human tasks. Not all robots can be said to be intelligent robots, however, and the field of robotics can be thought of as overlapping with the field of AI, rather than as an enclosed subset. At the intersection of robotics and AI are highly autonomous robots, which are able to perform tasks without direct human intervention [166].

Robotic autonomy can be subdivided into perceiving, planning, and execution [167], with each stage able to facilitate the next. Perception covers the ability of robots to learn from sensory data, with examples including object detection and voice recognition [168]. The ability to sense an environment can be provided by integrated sensors or computer vision techniques. In infrastructure, computer vision-enabled robots have been used to identify damage to dams [169], hazards to power lines [170], and road positioning for self-driving cars [165]. Planning tasks typically utilise the sensory data gathered through perception, reasoning from knowledge in order to decide which actions to take. Path and motion planning are some of the most common challenges, and are increasingly required in the growing field of swarm robotics, where a number of robots co-ordinate their behaviours to achieve a collective aim. Automated reasoning and machine learning techniques can help to enable intelligent autonomous planning, with examples in infrastructure including path planning using deep ESNs for unmanned aerial vehicles in wireless networks [171], and intelligent ontology-based planning for autonomous underwater vehicles [172]. Although fully autonomous robots require further research, robots with integrated artificial intelligence tools can execute of complex challenges, such as driving [173] [165], with high degrees of autonomy.

2.3.2.1 Natural Language Programming (NLP)

Natural language programming (NLP) concerns the interaction of computer systems with human language, in the form of speech and text. Techniques used in this branch of AI centre around syntactic analysis, which deals with the association of natural language and grammatical rules, and semantic analysis, which attempts to make sense of words and sentences. The topic of natural language processing can be further divided into the fields of understanding and generation.

Natural language understanding seeks to allow machines to comprehend written texts or unstructured language data. Speech recognition is often treated as a separate field, as it deals with the additional challenge of converting speech to text [174]. An ideal natural language understanding system would be able to paraphrase, translate, answer questions relating to, and draw inferences from, the content of an input text [175]. On the other hand, the goal of natural language generation is to enable computer systems to take structural data and produce natural language text, which may then be converted to speech if desired. The utilisation of NLP in infrastructure has been very limited, with the few existing examples primarily concerned with natural language generation. A bilingual natural language-based route advisor for public transport has been proposed [176], while recent work in the energy sector generates custom advisory reports based on the characteristics and priorities of household consumers [177].

Characteristics of Machine Learning Methods

With numerous machine learning tools available, and further subtypes of each, the justification for selecting one method over another is not always immediately evident. Presented below are the most common machine learning methods utilised in infrastructure systems and discusses the characteristics of each. Examples are drawn from various sectors to demonstrate how the traits of a given method contribute to its suitability for the desired application.

ANN

Strengths: ANNs are a versatile approach to solving complex, non-linear problems [178]. ANNs can be fault tolerant, and so are able to solve problems despite some failure elements on the network. After training, an ANN is able to produce an output even if presented with incomplete data [179].

Weaknesses: ANNs are a black box approach, and thus the structure of an ANN cannot provide insight into the function being approximated. ANNs require training, which can be time-consuming, and their effectiveness can depend on access to sufficient quantities of training data. ANNs can require retraining over time [179]. ANNs can suffer from overfitting and local minima issues [143].

Example of effective use: ANNs have been applied to the short-term forecasting of vehicle traffic flow, where they have outperformed traditional methods due to the stochastic nature of traffic flow and highly nonlinear characteristics of short-term prediction. Able to approximate functions regardless of non-linearity and without prior knowledge of functional form, ANNs have demonstrated the ability to predict vehicle count accurately even if vehicle category and corresponding speed are considered separately as input variables. ANNs also perform consistently across variation in time intervals [180].

Deep learning

Strengths: The problems where deep learning outperform traditional machine learning techniques are those involving very large quantities of data. Deep learning has proven to be very successful for high-dimensional datasets with very noisy data problems, such as image classification, natural language processing, and speech recognition [157].

Weaknesses: As a large quantity of data is typically required to train deep networks, problems where limited data is available may be unsuitable for this approach. Working with large datasets, in addition to the increased computational complexity of deep ANNs, often results in longer training and processing times, which are of particular concern for real-time applications [181]. Deep learning requires a higher standard of hardware than many other methods. As with most machine learning techniques, deep learning is a black box approach.

Example of effective use: Deep learning has been shown to improve upon conventional open shortest path first (OSPF) protocol for packet routing in telecommunications. With network traffic becoming increasingly complex, deep learning offers a smart strategy that is capable of considering multiple network parameters, outperforming traditional routing methods that consider only a single network parameter. Deep learning techniques can reduce overall packet loss rate and average delay per hop [182].

SVM

Strengths: SVM can solve the nonlinear problems while using small quantities of training data. While both ANN and SVM can solve the nonlinear problems, SVM only requires a small quantity of data to do so [179]. SVM methods are able to effectively handle data with both high degrees of uncertainty and heterogeneity [183]. SVM classifiers typically run at good speeds [143].

Weaknesses: SVM is a black box approach, so the intrinsic relations between inputs and outputs cannot be completely known [183]. This is as it is a kernel method, so has a maximum of one parameter per training data sample, rather than per variable. SVM has limited tolerance to noisy data or data with missing values, and can be susceptible to overfitting [143].

Example of effective use: SVM methods have performed consistently well in load and demand forecasting for the energy sector. In many energy forecasting scenarios, SVM techniques have consistently yielded lower mean absolute percentage error (MAPE) values than other machine learning methods, including ANNs [179]. The focus on empirical risk minimisation, rather than the "expert rules" learning technique of ANNs, enables SVM models to achieve accurate load forecasting in a relatively short time [184].

RF

Strengths: RFs are a versatile method, able to handle binary features, categorical features, and numerical features. There is very little pre-processing that needs to be done for RFs. The data does not need to be rescaled or transformed. RFs are able to handle noisy datasets, as well as those with missing values [152]. RFs do not suffer from overfitting, and are the fastest tree-based technique [143].

Weaknesses: RF is another black box approach (though not as much as other methods, as variable importance can be extracted from results). RF’s execution time, though typically low, can significantly increase with large volumes of data [185]. RFs for large datasets can also take up large amounts of memory.

Example of effective use: RFs outperformed numerous other machine learning classifiers in the modelling of travel mode choice. The high accuracy of tree-based ensemble classifiers indicates that the flexibility which is obtained by combining multiple trees is particularly useful for modelling transport choice. The dominance of RF over other tree-based classifiers can be attributed to the larger diversity among the learned trees of RF, which is a result of the RF’s procedure for randomised splitting at nodes [186].

K-means

Strengths: K-means is a scalable, rapid, and simple learning algorithm, able to handle large quantities of data [187].

Weaknesses: The simplicity of k-means comes at the cost of high sensitivity to initialisation - the user must provide a number of clusters without necessarily knowing what an effective number of clusters will be. K-means can also struggle with clusters of a ‘non-convex’ nature [154].

Example of effective use: K-means clustering has been effectively applied to data congestion control in vehicular ad hoc networks (VANETs). A closed-loop congestion control strategy utilised k-means to cluster the messages, with a control unit then determining parameters for each cluster, which are sent to vehicles stopped at intersections. This approach outperforms numerous existing methods, reducing packet loss ratio, average delay, and collision probability. This strategy also increased average throughput and packet delivery ratio considerably [187].

2.2.4 Findings - Purposes

The reasons for investigation and adoption of AI methods include system provision (of network capacity), forecasting, routing, monitoring and security, and improving the quality of resources or services. This section reviews the main purposes across infrastructure sectors to which AI methods have been applied.

2.2.4.1 System Provision

AI tools can be used to assist in the delivery of infrastructure systems, both in the sense of adding to generation capacity through the creation of additional supply sites, and in facilitating the provision of new independent networks.

A. Site Selection

In the oil and gas sector, comprehensive review papers discuss the potential of robotics in exploration and site selection [188] [189]. Research regarding applications has, to date, been limited to establishing the capabilities of UAVs [190] and autonomous underwater vehicle (AUVs) [191], and although these machines are becoming increasingly autonomous, there remains work to be done on developing truly intelligent robotics in the field of site exploration.

However, robotics is not the only category of AI used by the energy industry in the site selection process. The use of fuzzy logic in renewable energy systems is reviewed [61], with the authors finding that this form of automated reasoning has been widely used to assess the suitability of potential solar [192] [193] [128] [194], wind [127] [195] [196] [197], biomass

[198] [199], hydro [200], and hybrid renewable energy [201] plant locations. Fuzzy logic is particularly appropriate to this application due to its ability to capture heuristic reasoning among individuals. This allows fuzzy models to combine energy generation forecasting with environmental, economic, and socio-political variables to account for factors such as job creation and social acceptability in the selection process [199].

Fuzzy logic has also been employed in site selection of water and transportation infrastructure, albeit to a lesser extent. Integrated fuzzy logic and multicriteria decision models are used to select the locations for a wastewater treatment plant in Kahak, Iran [129], and a solar desalination plant on the Caspian sea coast [202], with both cases considering a spectrum of criteria ranging from land use and geology to distance from roads, rivers, and settlements. This approach is also employed to identify potential sites for car parking infrastructure [203] [204] and for electric vehicle charging stations [205]. This limited body of work demonstrates how other infrastructure systems could benefit from the flexibility of fuzzy logic as a decision-making tool for site selection.

B. Dynamic Network Creation

In the field of telecommunications, recent work proposes the use of AI-enabled UAVs as mobile aerial base stations, providing a wireless network for cellular users. As communication networks transition to 5G, UAVs can offer a dynamic approach, intelligently positioning themselves to offer an efficient and cost-effective service that can overcome challenges including random fluctuation of wireless channels, blocking and user mobility effects [206].

A number of machine learning approaches have been applied to facilitate effective network provision through UAVs. A machine learning framework based on a Gaussian mixture model (GMM) is utilised to predict network congestion, for the purpose of deploying UAVs in a way that minimises power usage for mobility and transmission [207]. A deep reinforcement learning approach, based on ESN cells, is employed to create a path planning scheme for cellular-connected UAVs, maximising energy efficiency and minimising both wireless latency and ground interference [171].

2.2.4.2 Forecasting

A. Supply forecasting

Supply forecasting covers the use of AI to predict the capacity of infrastructure systems, and by extension their ability to meet expected demand. Both automated reasoning and machine learning tools have been applied to supply forecasting in the energy sector. Fuzzy logic, ANNs, SVMs, RFs, deep learning, and hybrid models have all been used to predict meteorological variables and associated power outputs in renewable systems [61] [208] [209] [210] [211] [212]. Solar radiation, wind speed, and rainfall forecasting allows researchers to assess the energy generation potential of current and prospective solar, wind, and hydropower energy sites [208] [213] [10]. A fuzzy logic model has also been used to estimate the potential electricity output of biomass plants based on their inputs at a regional level [214]. Outside of renewables, an ANN-based approach outperforms traditional methods in forecasting oil, gas, and water production rates for a hydrocarbon reservoir [215].

In the water sector, the forecasting of available water is crucial to effectively managing resources. While the forecasting of variables such as groundwater level can give an indicator of supply levels [216], both machine learning [217] and deep learning [218] have also been applied to the more direct measure of reservoir inflow forecasting. This is an application where the size of the dataset can vary [217], which is an important factor to consider when choosing between standard machine learning methods and deep learning, which favours large datasets.

Forecasting the quality of potable water supplies is an emerging area of research [219], with ANNs performing well on case study data [220]. In sewage systems, where accurate sensing of chemicals can be very challenging and time consuming, a deep learning-based approach has been applied to the forecasting of water quality, achieving greater accuracy than traditional forecasting methods [221]. In more specialised applications, ANNs and SVM perform well when applied to water quality forecasting of groundwater for irrigation purposes [222] and of marine water for coastal hydro-environment management [223]

A hybrid approach incorporating machine learning has been employed to predict available ship supply in the freight industry [224]. By forecasting future destination, arrival and anchor time for each ship, it is possible to assign each journey to a suitable vessel and establish the number of available vessels in a given region. An alternative to machine learning, Markov decision processes, is judged superior to ANN and SVM approaches to destination prediction. As a result, the final hybrid approach uses Markov decision processes for destination forecasting, and extreme gradient boosting, a machine learning system based on DT models, to predict arrival and anchor times.

B. Demand forecasting

AI methods, dominated by machine learning, have been incredibly widely used in demand forecasting for infrastructure systems. Table 6 summarises the machine learning techniques applied to demand forecasting in each paper reviewed.

Numerous papers and several review papers examine the use of machine learning in energy demand forecasting. The majority of work to date takes a supervised learning approach, with ANN and SVM the most common methods used [225] [226] [227] [228] [142] [179] [143] [229] [230] [10] [231] [232]. An alternative approach, combining genetic algorithms, ant-colony optimisation and fuzzy logic, suggests that an expert systems-based approach can rival the prediction capabilities of ANNs in this area [233]. Recent work explores deep learning as a forecasting tool [138] [234] [235] [236] [237], with evidence suggesting it outperforms standard machine learning methods [238]. Hybrid methods have also become more common in recent years, with a variety of combinations incorporating both traditional techniques, machine learning, and deep learning methods [244] [245] [246]. While most work focuses on general energy demand, specific studies apply machine learning and deep learning-based models to demand forecasting of crude oil [247] and natural gas [248] [249].

Many of these machine learning techniques are also applied to water demand forecasting, with ANNs again dominating among chosen methods [250] [251] [208] [252]. Comparative studies show ANN-based approaches capable of achieving greater accuracy in water demand prediction than other machine learning systems [253] [254]. However, recent work has sought to apply deep learning and wavelet-based models to this task, yielding promising results for urban demand forecasting at the 15-minute [255], hourly [137] [255], and daily level [256] [257].

At the water-energy nexus, a tool for predicting energy and water demand in irrigation systems utilises both ANNs and genetic algorithms in the developed model [258]. While traditionally the optimisation of irrigation energy and water use has necessitated access to data from a wide range of sources and experts, the proposed model combines AI with satellite remote sensing to allow a more rapid response to changing conditions [258].

Demand forecasting in telecommunications can be split into two categories: traffic and churn forecasting. Regarding the former, machine learning and automated reasoning have been used to forecast call volume in a university network through a recurrent fuzzy-neural model [259] [260], while ANNs have been utilised to predict incoming requests in call centres [261] [262] and to forecast traffic in telecommunications networks [263] [264]. Much of the recent work in the field of telecommunications focuses on the application of machine learning to forecasting in 5G networks [266], with deep learning increasingly common in this field [267] [139]. Customer churn describes the movement of consumers away from a given supplier, and there is significant use of machine learning for churn forecasting in the telecommunications industry. An SVM-based approach shows the highest accuracy of common machine learning methods [268].

The transportation sector sees machine learning applied to traffic, destination and mode choice forecasting [62], each a factor in anticipating network demand. ANNs have been used to predict traffic flows in road networks [180] [269] [270] and combined with deep learning to predict citywide car, taxi, and public bike share traffic flows [63] [271] [272] [273] [274] [275] [276] [277] [278] [279] [280] [281]. In aviation, a LSTM-based model is able to predict air traffic well, despite anomalies in traffic control [285]. It is worth noting that the application of forecasting can be very time-sensitive, and so the run time of machine learning techniques is a significant factor to consider in the feasibility of these solutions. Finally, mode choice prediction can be used to gain an understanding of the factors influencing individuals' transport choices. A range of machine learning tools have been applied to this purpose, but a majority of comparative studies show a RF classifier gives the greatest accuracy [153] [286]. Results find journey length to be the most important variable in transport mode selection, although climate is also seen to contribute significantly [186].

Recent work at the energy-transport nexus looks into forecasting transportation energy demand [229] [287] [288] [289] [290], with some going further to consider both energy demand and CO_2 emissions [291]. With the increasing popularity and affordability of electric vehicles, forecasting of electric vehicle charging demand is a growing area of research, with the aims of minimising stress on the energy grid and reducing the cost of electric charging [292]. Deep learning-based methods are shown to be the best-performing methods for this application [293] [294] [295].

Table 6: Machine learning methods used in papers on demand forecasting. Only papers which proposed their own techniques are included. ○ indicates that a given method was utilised by the paper, while ● indicates the best performing method (where multiple techniques were applied to the same problem). E, W, T and C correspond to energy, water, transport and telecommunications respectively.

Reference	**Sector**	**Machine learning Method**								
		ANN	***SVM***	***DT***	***RF***	***K nearest neighbour***	***K-means***	***DL***	***Hybrid***	***Other***
[226]	*E*	○								
[186]	*E/T*	○								
[227]	*E*	●			○					
[81]	*E*	○							○ ANN + FL	● Genetic Algorithm
[138]	*E*	○	○					●		
[234]	*E*							○		
[236]	*E*	○						●		
[237]	*E*		○	○	○			●		
[238]	*E*	○	○					●		
[135]	*E*	○								
[231]	*E*	○	○		○				● ANN + firefly algorithm	
[232]	*E*				●	○				
[79]	*E*	○	○	●	○	○				
[233]	*E*			○	●					

[188]	*E/T*	○								
[187]	*E/T*								○ ANN + FL	
[289]	*E/T*			●			○			
[290]	*E/T*							●		
[234]	*W*	○								
[251]	*W*	○								
[253]	*W*	○								
[254]	*W*	○	○		○	●				
[137]	*W*	○	○					●		
[259]	*C*								○ ANN + FL	
[260]	*C*								○ ANN + FL	
[261]	*C*	○								
[262]	*C*	○								
[263]	*C*	○								
[264]	*C*	○	○					●		
[265]	*C*	○								● Gaussian Process
[266]	*C*	○					○			○ Gaussian Process
[267]	*C*							●		
[139]	*C*							●		
[268]	*C*	○	●	○						○ Naïve Bayes
[180]	*T*	○								
[269]	*T*	○								

[270]	*T*	○	○						● ANN + ARIMA	
[271]	*T*	○		○				●		
[272]	*T*							○		
[273]	*T*	○						●		
[274]	*T*	○						○	● DL + Bayesian	
[275]	*T*	○				○		●		○ Bayesian Gaussian tensor decomposition
[276]	*T*	○	○					●		
[277]	*T*							○		
[278]	*T*		○					○	● CNN + gated recurrent units	
[282]	*T*		○					●		○ Gaussian Process
[283]	*T*	○						●		
[285]	*T*		○					●		
[286]	*T*		●	○	●	○				
[186]	*T*	○	○	○	●					○ Naïve Bayes
[291]	*E/T*	○	○					○		
[245]	*E*	○							●	

									ANN + Discrete Wavelet Transform + Particle Swarm Optimization	
[246]	*E*								○ CNN + DL + Grey wolf optimization	
[244]	*E*								○ ANN + Bayesian optimization algorithm	
[239]	*E*		○					○		
[258]	*E/W*								○ ANN + Genetic algorithm	
[294]	*E/T*	○						●		
[292]	*E/T*							○		
[293]	*E/T*							●		
[295]	*E/T*							○		
[255]	*W*	○						○	● Wavelet + CNN-LSTM	

[256]	*W*								● Wavelet + Principal Component Analysis + LSTM	
[257]	*W*	○	○		○				● Wavelet + RF	
[252]	*W*								○ ANN + Genetic algorithm	
[280]	*T*	○		○				●		
[281]	*T*							●		○ Gaussian Mixture Model
[232]	*E*	○								
[248]	*E*	○						○	●	
[249]	*E*									
[247]	*E*								○ ANN + Genetic algorithm	
[284]	*T*	○						●		

C. Price forecasting

Although an extensive range of machine learning methods are used in energy price prediction [296] [297] [298], reviews find ANNs and SVMs to be the most popular [143] [299]. While the forecasting of crude oil [300] [301] [302] [303] and electricity prices [304] dominates the work in this field, it is found that a handful of papers predict the prices of other energy commodities such as fuelwood, natural gas [305], and carbon prices using machine learning [306]. Deep learning sees widespread use in the projection of electricity prices [307] [308] [309] [310], but has only more recently been applied to the crude oil equivalent [311] [312] [313]. Recognising that energy demand patterns changed in a rapid way during the COVID-19 pandemic, several studies apply machine learning methods to the prediction of energy prices [314] [315] and crude oil prices [316] during the pandemic.

ANNs [317] [318] and RF regressor models [151] have been utilised to predict water trade prices for Australia's Murray river basin and the Western United States respectively, enabling participants to make more efficient decisions in the face of uncertain asking and offering prices.

Several machine learning methods have been applied to the forecasting of used car prices, with gradient boosted DTs performing well [319] [320] [321]. Although this more directly represents an application of machine learning at the unit (vehicle) level, rather than the network level, it could be reasoned that they used car market has a relationship to both the adoption of electric vehicles and the development of reliable public transport networks. Hence there is a need to develop methods further to explore these complex dynamics. One novel application in the transport sector sees gradient boosting DTS used for the forecasting of road prices in Japan, where road prices represent an indicator used to determine Japan's fixed asset tax [322].

D. Safety forecasting

In the transportation sector, machine learning methods have also been applied to forecasting of road accidents and casualties [63] [323] [324] [325] [326] [140]. One novel study applies a deep learning ensemble method to the forecasting of traffic accidents using social media data, which can provide real-time and detailed information on road traffic accidents [327]. Another unique approach sees RF combined with the Gaussian distribution method to forecast road traffic 'black spots', with the aim of providing warnings to system users travelling in unfamiliar locations [328]. Though accident forecasting is largely focussed on accidents involving one or more road vehicles, there is also consideration of pedestrian fatalities due to road vehicles [329].

Both machine learning and deep learning-based methods can be used to forecast the severity of road traffic incidents [62] [330] [331]. Comparative studies, which compare multiple machine learning algorithms as well as single and ensemble-based methods, find RF and DTs to be among the best performing methods [332] in both single and ensemble machine learning methods, while ensemble methods are found to have greater accuracy than single methods [333]. Distance between vehicles and various weather variables are found to be the most significant factors influencing accident severity [334].

There have been recent efforts to apply accident forecasting outside of road traffic accident forecasting. A CNN-based model is found to outperform other machine learning methods including RF and DTs in the forecasting of accidents at highway-rail grade crossings [335], while in the maritime sector, a stacked machine learning model outperforms individual models such as RF in forecasting accident density and accident severity in areas of the Fujian sea [336].

2.2.4.3 Routing

A range of machine learning methods have been applied to telecommunications routing, the process of selecting paths to send data packets within or across networks [337] [182] [338] [339]. Optimal routing processes minimise delays and improve quality of service. In WSNs, a routing protocol using an unsupervised ANN in the form of a self-organising map (SOM) performs favourably when compared to existing routing methods, especially in scenarios with high levels of node failure [340] [341]. In opportunistic networks, where link performance is subject to high variability, ANNs and DTs have been successfully applied to routing [342], although more recent work claims that a Gaussian mixture model approach outperforms existing machine learning tools [343]. Deep learning has also been applied to routing in both wired and wireless networks, where several supervised and reinforcement learning methods are shown to reduce delays and improve throughput [344] [345].

Recent developments in the field of telecommunications have seen a move away from hardware-based networking, with a new software-based approach offering greater automation by de-coupling the control and data planes. Reinforcement learning is the favoured tool in recent work on routing in software defined networks (SDNs) [346], often in combination with deep learning architecture [347] [348]. An alternative, supervised deep learning approach is applied to SDN routing in order to minimise end-to-end delay in virtual network function section [349].

At the intersection of telecommunications and energy is the need to consider efficient load balancing through the development of 'green' or 'energy-aware' routing techniques that reduce energy consumption and prolong network lifetime in wireless sensor networks [350] [351] [352]. A variety of machine learning-based techniques, including deep learning and reinforcement learning, show potential in developing intelligent energy-efficient routing strategies, due to their ability to respond rapidly to environmental changes and integrate multiple factors into routing decisions [350] [353] [354]. Fuzzy logic has also been applied to green routing and is effective in allowing the consideration of various factors including the routing parameters charge, residual energy, and expected transmission count [351] [59].

VANETs are an instance of telecommunications being used in the development an intelligent transport system. These wireless networks connect moving and stationary vehicles, allowing exchange of information between vehicles and infrastructures in order to facilitate the safe, efficient and environmentally-conscious flow of traffic. A variety of machine learning approaches have been applied to routing in VANETs [355], including supervised ANN and SVM methods [356] [144], an unsupervised k-means approach [357], and deep reinforcement learning [155].

Machine learning extends to urban road traffic routing [62] [358] [359] and ride-hailing service vehicle pairing [360]. Routing in transport can be extended to include technologies that facilitate the independent navigation of autonomous vehicles. This is an emerging area of research, which often combines machine learning and robotics to enable safe movement of vehicles. AI supports three primary functions in autonomous road vehicles; perception, localisation and mapping, and decision making [362] [363] [165] [173] [364] [365]. To date, most of the work in this field is at agent, rather than system, level [361]. At the network level, however, security concerns can emerge from the use of machine learning techniques in connected systems of autonomous vehicles, and more research is needed to ensure their robustness to attack [366].

In examples from the shipping sector, data from an extensive network of shipboard sensors has been used in conjunction with a CNN to enable safe, autonomous navigation through a route containing multiple hazards [367], while fuzzy logic can support dynamic decision-making for autonomous navigation through international shipping routes [368].

In public transport, an interesting case study applies an ANN and SVM to campus shuttle bus route optimisation in a study that also considers fuel efficiency and vehicle emission, finding that the ANN yields better results for both peak and off-peak travel [371].

2.2.4.4 Monitoring and Security

This topic covers the use of AI for the purpose of maintaining a safe and effective infrastructure network. This includes inspection and preventative maintenance and extends to fault and hazard detection and response.

A. Inspection and Monitoring

In various infrastructure sectors, robotics has been utilised for inspection purposes. This has proven especially beneficial in the energy sector, where inspections can be necessary in hostile environments, such as nuclear environments [372] [373], but many systems are still heavily reliant on human operators. In the oil and gas industry, robots have been used for years for the inspection of assets [188] [189], but utilising their full potential requires a greater level of autonomy. Recent work seeks to automate the planning process of AUVs used in offshore oilfields, using an intelligent knowledge base to allow strategic planning that accounts for unexpected obstacles, in the absence of human input [172]. Outside of energy infrastructure, work has been done on the design of autonomous robots for bridge maintenance and inspection [374].

Other AI methods can aid robots undertaking inspections. For example, a machine learning-based computer vision approach has been integrated with UAVs to identify, map out, and monitor electrical infrastructure, which the authors suggest could be used to prepare preventive maintenance in the event of tree branches encroaching on power lines [170]. While computer vision has been applied to vegetation detection in electrical infrastructure, it's potential to detect defects in cables or insulation remains undeveloped [375]. UAVs have also been combined with machine learning methods for the systematic inspection of solar plants [376]. In aquatic environments, unmanned underwater vessels have been used to monitor dams and their surrounding ecosystems, utilising a computer vision approach to detect rock slides and cracks, as well as monitor native and invasive fish species [169]. In the transport sector, UAVs have been combined with CNNs for the purpose of detecting cracks and potholes on road network, with the UAVs able to move autonomously by also tracking the yellow line [377]. Road inspection is a complex challenge, with CNNs and other deep learning-based methods showing the most potential in this field [378].

Independent of robotics, machine learning has been applied to structural health monitoring of infrastructure. Examples of methods that can be applied in a range of infrastructure systems include computer vision–based crack detection in steel and concrete structures [379] and a deep learning approach to dealing with anomalies in sensor data [163]. A review covering machine learning for structural health monitoring in wind turbines shows that a range of supervised and unsupervised methods can be used to identify blade delamination, mud and dirt build-up, and loose bearings [380]. RFs and DT algorithms show high effectiveness in predicting anomalies in wind turbine function, informing preventative maintenance strategies [381]. Utilising both machine learning and automated reasoning, ANFIS has been applied to health monitoring of a full wind energy generation system, with the author suggesting a similar approach may be effective for photovoltaic or other generation systems [382]. In the oil and gas sector, a variety of machine learning and deep learning-based methods have been explored for fault prognosis, detection, and diagnosis, with a Gaussian mixture model found to be most effective in clustering risk of failure [383].

Machine learning has been employed to identify abnormalities in a water distribution network, with examples using machine learning tools alone and in combination with automated reasoning [384] [385] [386]. In another contribution to the development of an intelligent water distribution system, an ontologies-based approach to decision support has been applied for the purpose of identifying and mitigating failures [115].

AI has been utilised for safety monitoring in transport networks, where a computer vision-based approach is explored for traffic infrastructure inventory creation and assessment [134]. Results indicate that it is possible to achieve at least semi-automated inspection of road signage. The stability of tunnelled roadways has been assessed using machine learning tools, with a hybrid ANN and particle swarm method proving most effective [387]. In railway networks, deep learning and CNNs in particular show promise in surface defect [388] [389] and fastener [390] inspection. Deep machine learning has also been applied to fault detection for high speed rail [391]. As the use of high-speed rail spreads around the world, deep learning shows great potential as it has the capacity to deal with massive amounts of unsupervised data.

B. Security and Hazard Detection

While inspection and monitoring covers damage to networks from general wear and tear, the use of AI for security and hazard detection purposes deals with the protection of infrastructure systems from potentially destructive hazards or deliberate attacks.

Automated reasoning has been applied to hazard perception, with a rule-based reasoning approach used for automatic identification of marine risks that may lead to the grounding or sinking of vessels [392]. A combination of automated reasoning and machine learning has been utilised in VANETs to detect rear-end collisions along a stretch of highway. An ANN can predict the position of moving vehicles with high levels of accuracy, while a fuzzy inference system is used to create a safety index that allows different levels of risk to be identified in the modelling of rear-end collisions [393].

In telecommunications, network security is a major consideration and has been the subject of a large volume of research in recent years [394]. In SDNs, a spectrum of machine learning techniques including ANNs, SVMs, DTs, RFs, k nearest neighbour and Naïve-Bayes classifiers have been applied to the detection of denial-of-service and intrusion attacks, as well as to identify vulnerable nodes and select an appropriate responses to threats [185] [395] [125] [124] [396] [397] [398] [399]. Deep learning tools have also been employed for security purposes in SDNs [400] [402] [156]. Deep learning methods, including CNN-based approaches and hybrid deep learning techniques, are shown to be highly accurate for multi-vector denial-of-service attack detection [403] [404] [405]. The use of machine learning in optical networks is reviewed, with Bayesian and cognition-based methods among those applied to anomaly detection, and supervised SVM, ANN, RF, and DT techniques used in failure management [123] [146].

Cloud computing allows on-demand access to computer system resources without direct active management by the user, often available to a large network of consumers. A selection of machine learning algorithms have been reviewed for anomaly detection in cloud infrastructures including primarily DT-based algorithms, as well as an RF classifier [150]. This study finds that all algorithms are able to predict anomalies with relatively high precision and recall measures, although this can be diminished when aging effects are considered. In a review of the use of deep learning in 5G networks, security is identified as a significant area of ongoing study [406], with growth in data bringing concerns regarding security and privacy [407]. For 5G mobile network architecture, where unpredictable traffic fluctuation is to be expected, a deep learning approach consisting of a DBN layer and separate LSTM recurrent network layer has been designed to detect anomalies and recognise patterns of cyberattacks [132]. This two-layer approach demonstrates an ability to self-adapt in real-time, based on the volume of network flows.

At the intersection of telecommunications and energy is the cybersecurity of smart-grids, which can be vulnerable due to their dependence on advanced information and communication technology. Machine learning, which can rely on adaptive baseline behaviour models, can be used to effectively detect other-wise unknown threats [408]. Deep learning methods have been applied to the detection of false data injection attacks in smart grid networks [409] [410], which can bypass many traditional bad data detection mechanisms [411]. The proposed deep learning methods can balance the need to identify such attacks with the need to preserve the privacy of data in the network [412].

2.2.4.5 Quality

A. *Water Quality*

AI has been used to assess and improve water quality at various stages of the water treatment cycle [413] [414] [415]. The bulk of work to date is concerned with water treatment facilities, which includes plants dealing with surface water, ground water, and wastewater.

Accurate assessment of incoming water quality is critical to designing effective water treatment facilities. As accurate and thorough sampling is not always possible, machine learning tools have been applied to the forecasting of water quality indicators. ANN-based techniques have been applied to the prediction of numerous water quality indicators, with dissolved oxygen, temperature, and biological and chemical oxygen demand among the most common variables assessed [416]. Looking at other machine learning methods, support vector regression is proven more effective than a regression tree approach to predicting key wastewater quality indicators across a range of drainage basins, though both are found to give robust predictions [417]. The value of fuzzy logic in quality assessment has also been established, primarily in fresh water systems [413]. Finally, a hybrid approach combining DTs and a shallow CNN is effective in analysing the pollutant levels of industrial wastewater [418].

Once water has entered a treatment facility, it is critical that operators know that decontamination methods are effective. A range of machine learning approaches have been widely utilised in water and wastewater treatment for the purpose of modelling pollutant removal, where nutrients, heavy metals, and persistent organic pollutants are some of the most common contaminants [419] [420]. While ANN-based methods dominate, techniques such as SVMs, RF, ANFIS, and deep learning are also successfully utilised, and hybrid methods that combine ANNs with other machine learning approaches show high accuracy and robustness [136] [421]. ANNs are also shown to outperform response surface methodology in predicting pollutant removal [422].

Another application of ANNs in water treatment is the modelling of membrane performance, where membranes are barriers that block certain substances from passing through, as part of the water cleaning process [420] [423]. This can assist with treatment plant design.

In wastewater treatment, the activated sludge process uses aeration and a biological floc composed of bacteria and protozoa to treat contaminated water. Machine learning approaches have been employed to assist in the understanding of this ecosystem, identifying some functional features that are crucial to the effective adaptation of activated sludge bacteria to the wastewater treatment bioreactor environment [152] [183]. As with other stages of the water treatment process, water quality monitoring is necessary throughout wastewater treatment, with ANN-based techniques among the most commonly used machine learning-based methods [424]. A machine learning framework explores the operational factors that most significantly influence effluent quality, with influent temperature and levels of total suspended solids in the aeration process found to have the greatest impact on effluent parameters [425].

ANN-based models are also proven reliable in predicting the efficiency of desalination technologies, which are concerned with the removal of salt from surface water, groundwater, or wastewater. Most work to date has focused on utilising such models to assist in the control of desalination plants [420].

In the development of knowledge representation in water systems, ontology-based approaches has been proposed for water quality management [426] [427]. In the field of potable water quality, a range of AI assessment techniques, including fuzzy logic and ANNs, are considered at the consumer level, where simple, accessible, and affordable techniques are preferred. While potable water is concerned with drinkable water conditions, much of the work to date focuses on groundwater [428] [429]. In a promising example of portable water assessment, a deep learning based mobile application platform employs a deep CNN to assess the presence of E.coli in water using an inbuilt smartphone camera [164].

B. *Quality of Service*

For telecommunication companies, providing a high quality of service is critical for preventing customer churn. AI has been applied to the assessment of consumer quality of experience, and is also used to improve network quality in a variety of ways [430].

Supervised machine learning has been applied to quality of experience assessment for smartphone users in cellular networks. Key performance indicators incorporate user-reported data on experience and accessibility with quality of service traffic measurements, to quickly and accurately predict end-user satisfaction. A range of classifiers are considered, with RF and DT-based models outperforming SVM, ANN, and Naïve Bayes approaches [149]. A quality of service-centred approach to classification of traffic flows in SDNs is proposed, with an SVM-based classifier assigning quality of service classes to traffic flows through a semi-supervised machine learning approach. Key factors such as delay, jitter, and loss rate are used to assign a quality of service class, which the authors suggest using to efficiently re-route extremely large continuous flows (known as 'elephant' flows) [145]. To meet the quality of service requirements of 5G networks, base stations need real-time optimisation of radio resources in time-varying network conditions. A deep learning-based framework finds that cascaded neural networks perform better than fully-connected neural networks in meeting quality of service requirements with given bandwidth allocation [431].

To predict quality of transmission in optical networks, case-based reasoning, SVM, and RF methods are among the machine learning methods that have been utilised [123]. An ANN approach achieves high levels of accuracy with microsecond response time, facilitating dynamic network operation [432].

Machine learning and automated reasoning tools are also applied to video streaming over wireless networks, where an ANFIS approach has been utilised for the purpose of improving picture quality [433], and in the application of fog computing to cellular networks. Fog computing seeks to position resources at the network edge, between the data source and cloud, to bring them closer to the end user and improve network efficiency. A fuzzy clustering algorithm is proposed for an unsupervised machine learning approach to selecting fog nodes in a 5G network, with the aim of reducing system latency [434].

2.2.5 Findings – Infrastructure sectors

The use of AI varies between each of the economic infrastructure sectors: energy, water and wastewater, transport, and telecommunications. This section reports on the use of AI methods in each sector and each pair of sectors, the latter recognising the increasing blurring of sectoral boundaries.

2.2.5.1 Energy

In the energy sector, AI tools have been extensively applied to demand forecasting [235] [138] [242] [225] [233], especially at residential and building level [226] [238] [142] [228] [179]. Further applications include price forecasting [143], demand side management [435], and the monitoring of electrical cable networks [170]. Facilitating energy use reduction is of increasing concern in this sector, and methods ranging from efficiency-centred ontologies [117] to natural language generation of consumer advice reports [177] have been utilised for this purpose.

Much of the rest of the work in the energy sector focuses on generation systems, where many of the most developed applications pertain to renewable energy infrastructure [436]. Robotics shows significant potential as an aid in the oil, gas and nuclear sectors, but the machines used to date remain limited in their autonomy [188] [189] [372]. In renewable energy systems, there has been increasing use of AI in supply forecasting. Key elements of this include meteorological forecasting, where ANN and fuzzy logic techniques are popular [437] [61] [438] [11] [439], and solar tracking, which often utilises computer vision tools [440]. Artificially intelligent methods of inspection and structural health monitoring for renewable energy assets have also been investigated [380] [382].

2.2.5.2 Water and wastewater

AI methods have been utilised across water networks, from initial water treatment through to distribution and consumer-related challenges. At the supply end, much of the research is concerned with water quality [426] [413] and pollutant removal [136], in both standard and wastewater treatment [417] [183] [152] [419] [423]. Machine learning methods have also been utilised in desalination, where they can have implications for plant design [420].

Deep learning has grown in popularity in the water sector in recent years, and has been applied to a variety of problems including runoff prediction, flood forecasting, groundwater modelling, water quality, and water treatment [441].

The use of robotics in water systems for inspection purposes has been largely limited to semi-autonomous machines [374], although computer vision-enabled robots have recently been successfully utilised to monitor assets such as dams [169]. In water distribution networks, both ontology-based knowledge representation [115] and machine learning techniques [384] [385] have been applied to the detection of bursts and abnormal flows.

From an end-usage perspective, a range of machine learning techniques, including ANNs, RFs, SVMs, k Nearest Neighbour, regression trees and DBNs, have been applied to water demand forecasting [254] [137] [251] [253] and price forecasting [317] [318] [151] across a range of geographic scales. A selection of machine learning and computer vision methods have been applied to quality assessment at consumer level [428], where smart-phone based approaches show significant potential as a widely accessible tool [429] [164].

2.2.5.3 Transportation

The transportation sector has seen perhaps the most variation in tasks to which AI has been applied [63] [62]. Looking at transportation networks as a whole, a number of knowledge representation systems, many ontology-based, are proposed [118] [442] [116] [443], while recent research into how the public interact with transport systems from a behavioural perspective, including transport mode selection, benefits from a range of machine learning techniques [153]. Although it is recognised that traffic flow and accident prediction can be utilised for a variety of urban transportation systems [273] [326], much of the remaining work in this sector has focused on individual modes of transportation.

Regarding road vehicle usage, a range of machine learning methods have been applied to traffic [269] [180] [272] [62] [279] and accident forecasting [325] [326] [140] [63] [62], as well as for navigational tools [62]. Similar tools have also been utilised in demand forecasting [271] [282] and destination prediction for taxi services [62] [360]. Several researchers have sought to apply AI to identifying and mapping road networks [444] [445] [446], whilst computer vision-based approaches to monitoring traffic infrastructure have been proposed [447]. In-vehicle and roadside sensors have the potential to provide more data on road networks than ever before, and deep learning methods are likely to play a significant role in the development of an intelligent transport network, with CNNs used in object detection, localisation, and classification for a variety of applications [448]. Work on the development of self-driving cars has seen massive interest in recent years, and automated reasoning [173] [364], machine and deep learning [363], and computer vision have all been utilised in what could be considered a primarily robotics-based challenge [165] [63] [362].

The application of AI in transport is not limited to the roads. Shipping and freight has seen increased interest in autonomous vessels [361], and efforts to facilitate autonomous navigation [367] and hazard awareness [392] are important steps towards this goal. Machine learning has also been applied to supply forecasting in the shipping sector [224]. Railway networks have primarily seen AI applied to inspection and monitoring purposes. Though robotics, and specifically UAVs, demonstrate much potential in the monitoring of railway assets, many are still reliant on a significant level of human interaction [449] [374]. Deep learning tools, however, prove themselves effective at surface defect [388] [389] and fastener [390] inspection, as well as fault diagnosis, in high-speed rail [391], which is expected to grow in popularity as a mode of travel. While most other work in public transport is primarily focused on traffic flows or choice of transportation method [62] [153], bus networks have been the subject of individual research, which focuses largely on scheduling issues [450] [451].

2.2.5.4 Telecommunications

Machine learning methods are seen as highly significant for the success of the next generation of wireless networks [131] [452] [453] [58] [454]. Research covers a variety of network types, with some works covering the more general ‘cellular’ or ‘wireless’ networks, and others focusing specifically on software-defined networks [455] [456] [457], optical networks [123] [146], 5G [131] [139] [266], and the cloud [150].

As in other infrastructure sectors, telecommunications has seen machine learning utilised in traffic and demand forecasting [259] [260] [263] [261] [262] [264] [266], with recent work focused on deep learning approaches [267] [139]. Another common application of machine learning, where all learning types have been employed, is in routing [340] [341] [342] [182] [347] [346] [343] [344] [345] [348] [349], where effective solutions can help reduce latency.

From a consumer perspective, quality of both transmission and overall experience are very important in telecommunication networks. Assessing customer experience and network quality, which can be dependent on factors including latency, jitter, loss rate and image or video definition, are active areas of research, utilising a range of machine learning classifiers [149] [432] [123]. The design of traffic clustering techniques that factor in quality of service has also been suggested [145]. Additionally, the accuracy of several machine learning methods has been compared in predicting customer churn [268].

Security is a critical concern in telecommunications, especially in wireless networks and SDNs [394]. A spectrum of machine learning approaches have been used in anomaly detection [123] [146] [150] [132], the identification of denial-of-service [125] [396] [403]

[405] and intrusion attacks [185] [395] [402], and for selecting an appropriate response [458].

Due to the increasingly wireless nature of telecommunications, it is possible to provide dynamic networks that utilise UAVs as mobile base stations. Although not yet widespread, it is anticipated that interest in this area will continue to grow, and research to date has looked at how to deploy UAVs effectively [207] [171].

2.2.5.5 Energy and Water

A range of AI techniques have been applied at the water-energy nexus, which describes the intersection of water and energy systems [208] [459]. Hydropower, the generation of electricity from directing water through a turbine, sits at this nexus as an example of water use for energy applications. Unsupervised k-means clustering has been utilised in modelling the distribution of hydropower facilities and nearby land cover, to estimate system evaporation [460]. Of supervised techniques, ANNs have been applied to hydropower reservoir inflow forecasting [438], while SVMs have been used to analyse the division between hydropower and irrigation in worldwide reservoir usage trends [461]. ANNs and genetic algorithms have also been incorporated into a forecasting tool for energy and water demand for the irrigation systems of water user associations [258].

On a consumer level, there are many systems that both utilise water and require energy, such as dishwashers, washing machines, and showers. Research applies machine learning tools, including SVMs [462] and Hidden Markov model combined with stacked autoencoders [463], to classify such water end-use events on a residential scale.

2.2.5.6 Energy and Transport

Energy demand forecasting for transportation has received less attention than equivalent forecasting for buildings, although researchers recognise its importance in the decarbonisation of cities. Machine learning techniques such as ANNs and ANFIS allow both transport and socio-economic indicators to be considered when predicting future demand [229] [288] [287] [289] [290].

AI tools have also been applied to electric and hybrid vehicles, the numbers of which are rapidly growing worldwide. Deep reinforcement learning has been shown to improve energy efficiency in individual units [464], while research at network level focuses on routing, charging point selection, and integration of electric vehicles into the smart grid [465], all of which can benefit from some level of local demand forecasting [466] [467] [293] [292] [294]. At the vehicle-grid intersection, minimising energy peaks can be done through load balancing, congestion pricing, and market selling and purchasing strategies [465].

2.2.5.7 Water and Transport

Though an area of minimal research, it has been recognised that water and transportation systems are not unconnected. In particular, abnormally intense periods of rainfall have the potential to cause significant disruption to rail and road transportation networks. This is an argument in favour of monitoring water levels in lakes and reservoirs, to which ANN methods have been applied [468].

2.2.5.8 Energy and Telecommunications

Recent work in telecommunications is beginning to recognise the significance of efficient energy usage in communication systems. Machine learning tools have been applied to energy-efficient resource allocation in cloud networks [469], and research on utilising UAVs to provide dynamic networks has prioritised low energy usage [207] [171] [470].

2.2.5.9 Transport and Telecommunications

VANETs, which facilitate dynamic wireless connections between vehicles, sit at the intersection of transport and telecommunications. As in other telecommunication networks, machine learning has been utilised in VANETs for routing [357] [144] [356] [155] and security [471] [472]. AI tools have also been used to improve VANET efficiency in the context of enhanced road safety, with ANNs and fuzzy inference systems applied to rear-end collision avoidance [393] and k-means clustering utilised to improve safety at congestion points such as intersections [187].

2.2.5.10 Water and Telecommunications

The research in this area is largely limited to flood prediction and mitigation, where the 'Internet of Things' wireless sensor network (WSN) has been combined with ANNs to predict flooding events [473] and communicate warnings for those at risk [474]. There remains an absence of work utilising AI to predict, assess, or mitigate the effects of flooding on telecommunications infrastructure.

2.2.6 Findings - Cross sectoral

2.2.6.1 Analysis framework

The structure of this cross-sectoral analysis is based on a framework proposed by Sharifi, which consists of 11 qualities with associated evaluation criteria [475]. This framework is concerned not only with innovative solutions, but effective implementation, which is often dependent on recognising the interconnections between systems and the interdisciplinary nature of work in cities and infrastructure [476]. Two additional criteria, comparison and vulnerability, have been added to the original framework in order to align the analysis with AI in infrastructure. Table 7 outlines how each criterion relates to infrastructure systems, as well as the extent to which each is satisfied by the overall body of research covered by this review. Criteria with limited coverage would benefit from greater consideration in future research in this field; this is explored more in section 2.2.7. Where possible, examples of a paper that meets the description of the criterion to a high degree are provided, as are examples which show a low level of sophistication in regard to a criterion, but do not neglect it entirely.

TABLE 7: ANALYSIS FRAMEWORK

Key	High coverage	Medium coverage	Low coverage

Quality	Criteria description	Extent of coverage	Low level example	High level example
Comprehensiveness	The extent of inclusion of indicators related to different themes (which can include the economy, society, governance, the environment, mobility, and data) and sub-themes in the selected tools.		Small range of indicators [471]	Multi-criteria, multi-dimension [196]
Stakeholder engagement	Whether participatory approaches (which include interviews, questionnaire surveys, focus group discussions, community workshops, and consultations) are considered in the development and implementation of the selected tools.		Includes opinion as an indicator [196]	High level of feedback [149]
Context-sensitivity	Whether the selected tools take account of user needs and context-specific needs and challenges.		Overview of method with examples [394]	Method adapted to context [282]
Strategic needs	Whether the selected tools are aligned with strategic needs and priorities. This includes attempts to evaluate performance against local or higher-level strategic targets.		Recognition of global strategic direction [139]	Looks at effects of policy [326]
Uncertainty management	Whether iterative processes are adapted and future scenarios are developed to take account of future uncertainties.		Automatic updates considered [444]	Adaptive technique [296]
Interlinkages and interoperability	Whether interlinkages and interoperability between different indicators and systems are considered in the assessment process.		Research at an area of overlap between systems [205]	Nexus between infrastructures [208]
Temporal changes	Whether selected tools track temporal changes.		Short-term forecasting [254]	Range of temporal scales and resolutions [238]

Flexibility	Whether issues related to flexibility, scalability, and replicability are considered by the selected tools.		Method specific to application [368]	Scalable and adjustable method [432]
Feasibility	Whether issues related to technical and financial feasibility are considered by the selected tools.		Financial feasibility recognised [429]	Multiple indicators to consider feasibility [201]
Presentation and communication	Whether the selected tools take appropriate approaches to effective presentation and communication of the results.		Short, clearly presented paper [434]	Good visualisations [274]
Comparison	Whether selected tools are compared against other methods, using a common dataset that is large enough to be representative.		Two models compared [152]	Several independent models compared [343]
Vulnerability	Whether potential failure methods are considered by the selected tools.		Improving network security [125]	Focus on failure identification [391]
Action-oriented approach	Whether assessment findings are used for developing action plans and broader infrastructure implementation roadmaps.		No examples found	No examples found

2.2.6.2 Comprehensiveness

There are examples of work in the field of infrastructure that consider a spectrum of influencing variables, with site selection research yielding some of the best. One example, investigating wind farm location, applies a total of 28 evaluation criteria across six dimensions; safety and quality, economy and benefit, social impression, environment and ecology, regulation, and policy [196]. The widespread utilisation of fuzzy logic for this application allows for the inclusion of variables with levels of uncertainty, such as average wind speed and intensity of natural disaster occurrence [197]. Site selection of electric vehicle charging stations, which also makes use of fuzzy logic, considers 11 sub-criteria within economic, social and environmental sectors [205].

In contrast, much of the work on forecasting considers only historical data of the same kind. While this will reflect a number of indicators, the research does not seek to identify them or quantify their contribution or significance. This means that should economic, social, environmental or other factors fluctuate outside of the range of what was experienced in training data, forecasts maybe be inaccurate. While systems with large volumes of training data will be less susceptible to fluctuations outside of training range, this method, seen often in demand forecasting, remains limited in comprehensiveness. An exception is transport energy demand forecasting, where a variety of socio-demographic indicators have been considered, including vehicle ownership levels and fuel prices [229] [288] [287] [289]. The inclusion of a range of variables is also seen in other forms of forecasting, with quality of experience forecasting in telecommunications assessing 12 key performance indicators [149], and water price forecasting taking into account a range of transaction, economic, demographic, meteorological and hydrological variables [151]. Passenger density, population size, and gross national product are among the input variables used in transport casualty forecasting [326] [325]. In customer churn prediction, up to 19 indicators centred on network usage, such as call frequency and duration, have been considered [268].

One area that shows significant range in variable comprehensiveness is network routing. While some approaches seek to optimise a single variable, typically network congestion or delay [356], other work incorporates 12 inputs, including buffer occupancy and success ratio [342], and seeks to account for multiple noise parameters [341].

Many instances of the use of AI in infrastructure are very subject specific. It may be argued that, even if cases where a single variable is the primary concern, multiple indicators should be considered if only to show their significance. However, it is the case that much research in infrastructure is concerned with a narrow selection of factors. For example, pollutant removal is concerned solely with levels of particular pollutants [136], and quality of transmission is often measured by latency [432].

Comprehensiveness, while not evidenced across the board, is a quality that has been demonstrated in a significant number of papers investigated, and it is expected that the benchmark will be raised as papers with a narrow range of indicators are outperformed by those with more comprehensive techniques. In select cases, however, focusing on a tight selection of variables may be beneficial, including instances of time-sensitive analysis or limited computational capacity.

2.2.6.3 Stakeholder engagement

Engagement through participatory approaches in infrastructure AI research has been scarce, with only a handful of instances discovered. Participatory approaches have been extended to include consultation with stakeholders in this context. A paper trying to assess quality of experience for telecommunication end-users combines a passive monitoring tool with a feedback application in participants' smartphones. In total, around 700 instances of feedback are recorded, which helps to establish relationships between quality of experience and several other performance indicators, such as length of session [149]. This approach shows significant potential and could be incorporated in customer churn prediction, which is heavily linked to user experience. Other examples of stakeholder engagement have been limited to consultation for the purpose of evaluating social indicators, such as consulting local residents during wind farm site selection [196].

2.2.6.4 Context-sensitivity

Many techniques explored in this review are applied to particular contexts, as the complex nature of machine learning tools often makes then unsuitable to broad circumstances. Several papers frame their findings in a context-specific way through the use of case studies [197] [438] [201] [151] [273], although it is worth noting that often no adaptation has been done to the method, rather a specific dataset has been used.

The best examples of context-sensitive research in this field incorporate context at the method level. In one very unique situation, which forecasts traffic accidents in Turkey, the potential for Turkey to become an EU-member state is considered as part of the variable selection process [325]. In another very context-aware case, time-series data is been combined with textual data for taxi demand prediction in event areas. The authors utilise online information regarding events scheduling at venues within the study area, recognising that this is likely to influence local taxi demand [282]. A final example attempts to establish the context in which the consumer is making decisions when generating energy-saving advice tailored to households [177].

2.2.6.5 Strategic needs

Despite the high relevance of many strategic plans to infrastructure systems, minimal research to date has taken a strategic viewpoint. Much of the work covered in this review could be used to inform policy or strategy, rather than the inverse of research being informed by strategy. A contributing factor may be the discrepancies in geographic scale, with a substantial quantity of research focused on specific applications or individual systems on a local level, while strategic plans often take a broader approach and deal with significant geographic areas and/or multiple systems. That is not to say that opportunities do not exist to incorporate strategy in this type of work. In one example, an effort is made to predict the impact of railway development policy on road casualties in Turkey [326]. Though not aligned with any stated strategic goal, a substantial body of recent work in telecommunications pertains to the widespread transition towards 5G [131] [132] [171] [139] [266] [469] [434].

2.2.6.6 Uncertainty management

While supervised machine learning has proven its effectiveness in a wide range of applications, other approaches may be needed to deal with the increasing uncertainty that comes with larger and more interconnected systems [464]. Several AI methods lend themselves well to uncertainties, including fuzzy logic and unsupervised learning. The iterative nature of reinforcement learning also allows adaptation to uncertainty.

Treating uncertain indicators as fuzzy parameters allows them to be considered alongside more concrete variables, with the probabilistic nature of this approach allowing levels of uncertainty to be considered. This has been effectively applied to variables in the selection of sites for assets such as wind turbines [197] and car parks [204].

Where uncertainties are in outputs, unsupervised learning can assist in identifying relationships and clusters in a given dataset without prior knowledge any links between data. The potential of unsupervised learning has been exploited for numerous infrastructure applications, including anomaly detection [156], churn prediction [477] and traffic clustering [266] in telecommunications.

One example in reservoir inflow forecasting uses historical forecast residuals to generate additional realisations on top of the initial point forecast, to account for uncertainties in hourly forecasts [438]. In another example, concerned with software attacks, an 'ambiguous' category is included, consisting of the most uncertain samples. The data that falls into this category is separately classified and used to re-train the model, offering more learning potential than clear-cut positive or negative scenarios [185].

Reinforcement learning is an inherently iterative approach, which thus lends itself well to dealing with uncertainty, and has seen increased uptake in recent years. Applications have included improving energy efficiency in vehicles [464], and routing in telecommunication networks [348].

2.2.6.7 Interlinkages and interoperability

As infrastructure networks can be considered a 'system of systems', interlinkages are an important part of infrastructure research. However, possibly due to the high level of subject-specific research and the limited extent of research that is broad in nature, the literature covered in this review is very restricted in its consideration of interlinkages and interoperability. Even the more abstract work in knowledge representation struggles to establish connections between different systems, although an attempt has been made to link different transport networks [118].

The limited recognition of relationships and dependencies between systems is evident in a review of the water-energy nexus [208]. Despite this nexus representing a significant overlap in systems, few papers sit in this region, and those that do are often very subject-specific, and thus typically deal with a narrow range of indicators. While the existence of this review, and its attempt to categorise papers into subgroups such as 'water-for-energy', is a promising step in this field, there remains a lack of research considering connections between the two systems, and an even greater absence of papers concerned with the intersection of other infrastructure sectors. Perhaps the only other significant area of interconnectivity research is the junction of energy and transport, where several papers have looked at the energy demands of transport [229] [288] [287] and other have considered the integration of electric vehicles into the smart grid [465].

2.2.6.8 Temporal changes

As one of the most extensively researched purposes, forecasting of various variables has been studied across a wide range of temporal scales and resolutions. It is worth noting that, for many machine learning methods, both temporal scale and resolution are dependent on the historical data available.

Illustrating the temporal scalability achieved by research to date, one study predicting energy consumption at building level is able to produce forecasts for 15 minutes, hourly, daily, weekly, or yearly intervals, at resolutions ranging from one minute to weekly, using 47 months of sampled data [238]. In different sectors, forecasting across a span of several years is not uncommon. For example, forecasting of road traffic causalities over a decade into the future has been attempted [325].

Despite the apparent accuracy challenges that arise when dealing with larger temporal scales, the inherent structure of many machine learning tools renders them valuable assets in learning from past data changes and using this knowledge to forecast future trends. It is also worth noting that forecasting is not the only purpose for which AI has been applied to the monitoring of changes over time. Computer vision tools in particular prove valuable in structural health monitoring, allowing the condition of assets such as bridges, dams and wind turbines to be assessed over time, and deterioration signs such as corrosion or cracks to be identified [169] [380].

Additional temporal elements to consider are training and operating speeds, which are particularly pertinent to real-time applications. For supervised learning, there is a training period, ranging from hours to days, required before the model has processed enough data to offer accurate predictions. Although this is an up-front activity, it can be necessary to re-train models over time as inputs change. Advances in the field of machine learning do offer alternative solutions given appropriate resources including semi-supervised learning or the ability to train 'as you go' by adding labels to incoming data [478].

The computational complexity of machine learning techniques also affects operating speeds. Therefore, papers addressing time-sensitive tasks should explicitly consider their method's run time, in addition to accuracy, as an indicator of performance. While the trade-off between complexity and running speed warrants consideration, it is worth noting that improvements in hardware, bandwidth, data transmission speeds and cloud computing make the adoption of AI more feasible than ever [479]. These improvements do not come without a cost, and this cost goes beyond the financial to include the carbon emissions associated with higher computational and data needs.

2.2.6.9 Flexibility

The flexibility of many of the machine learning techniques utilised in infrastructure is promising. Ultimately, the vast majority of models can be adapted to a range of conditions, provided adequate training data is available. A change in conditions may include a new geographic location, increased or decreased significance of input variables, or changing relationships between input variables. Flexibility goes hand in hand with feasibility for machine learning, as computational expense increases with the complexity of the model.

In terms of scalability, the forecasting undertaken by machine learning tools for infrastructure purposes has spanned a range of geographic scales. For example, energy demand has been estimated at building level [242] [238], and for the whole urban area of Sydney [241]. Research in the field of telecommunication networks, which are increasingly moving away from hardware and towards software-defined architectures, recognises the need to consider scalability in a range of applications [338], including intrusion detection [471] [395], quality of transmission [432] and traffic forecasting [139].

It is worth noting that other areas of AI face different issues with flexibility and scalability. In knowledge representation, for example, structuring large quantities of concepts, relationships and interdependencies is a significant challenge. If a true 'system of systems' approach is to prevail in infrastructure, knowledge representation systems must be developed that can encompass a great number of interconnected networks.

2.2.6.10 Feasibility

Machine learning techniques, particularly deep learning methods requiring large datasets, have the potential to be very computationally expensive. In time-sensitive environments, the computational power required to achieve a result quickly enough may be prohibitively expensive. While model accuracy is important, run-speed, especially as compared to alternative techniques, is often also a very significant factor [240]. While a few papers allude to such reasons as justification for selecting one method over another, feasibility is rarely considered beyond this.

Other examples of studies that consider feasibility include the use of smartphones to allow consumers to assess water quality, demonstrating an awareness of the financial constraints many end-users face that may prohibit more complex technology [429]. Feasibility concerns may also extend to include the priority of energy-conservation in UAVs used for network provision, where excessive energy cost or recharging requirements may impact viability [171] [207]. While feasibility is considered in these cases, it is worth noting that it is in a qualitative sense, with no research reviewing the feasibility of a proposed method in a systematic or quantitative sense. While feasibility can include financial viability, applications dealing with physical infrastructure can often experience other concerns. In the selection of renewable energy sites, for example, exposure to energy source and appropriate ground conditions are crucial for providing adequate energy generation, while public support can be key to getting projects approved. These variables can be quantified, and included as inputs in the site selection process [201].

As regards technical feasibility, one of the core requirements of machine learning systems is access to sufficient training datasets. While research may yield promising findings for a given dataset, if an adequate supply of training data is not available for the desired application, many machine learning methods are not technically feasible in that context.

2.2.6.11 Presentation and communication

As journal or conference papers are selected for this review, the quality of written communication is high across the board. A range of figures and graphs are used to aid understanding, with comparative studies often using graphical methods to highlight the differences between different models or techniques [149]. As mentioned earlier, a substantial number of papers also use case studies to demonstrate their findings.

2.2.6.12 Comparison

The studies reviewed, particularly those that fall into the category of machine learning, encompass a large range of models, many of which seek to outperform traditional methods. In order to demonstrate a solution is effective, many researchers either compare their work to existing models or set out to find the best method out of several contenders, using variables such as accuracy, speed, and sensitivity to judge performance [149] [186]. An important caveat to this is that the comparative indicators selected tend to be overwhelmingly technical in nature. While this is a valuable gauge of ability, it is not the only measure of success. There are also economic indicators, such as set-up and operating costs, and planning or governance concerns, such as compliance with regulations and the ease of training others to use a model, that, while beyond the scope of many engineering papers, must be considered if there is to be widespread uptake of these methods in government and industry.

There is variation in comparative scope across the literature. Some work takes a straightforward approach, comparing a proposed method solely with the actual outcomes it attempts to predict [137]. Others run a model both with and without the addition of a machine learning technique, demonstrating the benefits of the AI approach [207]. It is not uncommon to find several types of ANNs measured against each other to find which is best for a particular application [235], while other papers include an even greater range of machine learning methods, such as SVM, RF, and DTs, in their comparisons [149] [268] [286] [186]. Ensemble methods, which combine two or more machine learning techniques, have also been compared to those using only a single technique [228]. Finally, a pool of several machine learning techniques and less complex methods, such as the historical average and ARIMA techniques for forecasting, have been applied and assessed for a given application [253] [272] [273].

It is worth recognising that, in order for comparison to be accurate, the dataset being used should be as similar as possible for each model, and of a substantial enough size to be representative. The vast majority of papers attempting comparison test each method on an identical dataset, which can span significant geographic and temporal ranges. Examples include forecasting for entire cities or regions [140] [273], and accident prediction based on years, and even decades, of data [325] [287]. There are also efforts being made in the computer science community to shift towards open-source code, to allow existing models to be used by others to validate results and compare performance with newer models. This is happening at the same time as a push to make more data open-source, which further promotes the benchmarking of new models against existing methods.

2.2.6.13 Vulnerability

The vulnerability of infrastructure systems concerns their susceptibility to both deliberate attacks and a variety of accidental causes of failure. The latter may include failure due to an imbalance in supply and demand, poor network management, or a breakage of physical infrastructure from poor maintenance or natural disaster.

As detailed earlier in this review, numerous papers apply AI to the purpose of security. The field of telecommunications has been at the forefront of this research, utilising a range of machine learning tools in the detection of intrusion attacks, network anomalies, and denial-of-service attacks [125] [395] [402].

Papers concerned with non-deliberate system failure are often less explicit in their discussion of vulnerability. However, it could be reasoned that there are far more variables contributing to accidental failure, making the breadth of this research much greater. For example, effective demand forecasting and traffic routing, purposes to which AI has been extensively applied, both contribute to the crucial balancing of supply and demand. There are also specific instances of research focusing on non-deliberate failures. These include the use of ontologies for failure identification and mitigation in water networks [115] and machine learning techniques for fault diagnosis in high-speed rail [391].

The fact that supervised machine learning techniques rely heavily on access to comprehensive training data is important in the discussion of vulnerability. If a model has encountered potential failure scenarios in its training dataset, it will have knowledge of these patterns and be better prepared should it face a similar situation during operation. This is only possible, however, if there are sufficient examples of previous instances which can be included in training data. The question of how to react to rare events, which occur so infrequently that their presence in existing data is sparse, is one that is crucial to the prevention of potential system failure. Several papers have approached this by teaching a model the normal state of a network and setting a boundary beyond which behaviour is considered abnormal and flagged [458]. Other techniques have begun to be developed [62], although more work in this area would be beneficial, particularly outside of the field of telecommunications.

2.2.6.14 Action-oriented approach

While a number of papers present frameworks [138] [145], and others offer case studies as practical examples [151] [197], no papers reviewed in this work include a formal action plan for system-wide implementation. It is worth noting, however, that much of the research described in this review is conducted in very specific fields or on small scales. Therefore, while findings may well be relevant to those creating action plans, they are not typically of a large enough scale to warrant the proposal of a plan independently.

2.2.6.15 Analysis findings

Infrastructure systems are inherently complex, and so it is promising that elements contributing to complexity - uncertainty management, interlinkages, vulnerability, and flexibility – are all developed to some extent in the reviewed work. This provides a strong foundation upon which researchers can build, to progress the implementation of AI across increasingly complex networks in towns and cities.

It is evident that some of the beneficial characteristics of AI are reflected in the areas in which the literature is well developed. Perhaps the best example is reinforcement learning which, as a technique designed to learn the optimal strategy from interaction with an environment, is inherently very specific to context [133]. It should also be noted that the significant majority of literature reviewed sits within the bracket of engineering or computer science. It can be argued that this contributes both to the strengths seen in this analysis and the areas in which there are gaps. Many of the proposed solutions value a strong quantitative performance, demonstrating this over a range of geographic and temporal scales, at various degrees of granularity. There have been very effective attempts to incorporate numerous quantitative variables in models which outperform traditional methods in many measurable ways. While this represents a significant strength, it is in the areas where it is more difficult to obtain such neat, measurable results, that the literature is less developed.

The sections of analysis where performance is more qualitative – stakeholder engagement, strategic planning, feasibility, and action-orientated approach – are typically of greater concern to those in planning, business, governance, and policymaking. While engineers can offer accurate and effective solutions, it requires the co-operation and insight of those in other sectors to bring AI from research into large-scale, interconnected projects in the real world. In addition to limited consideration of non-engineering sectors during the design stage, the technical knowledge required to create and sustain AI-based solutions presents a significant barrier to implementation in many areas of industry. It has been noted that investment in people, skills, and processes is necessary for the widespread uptake of AI [479]. These gaps highlight the importance of collaboration with other disciplines, such as economics, planning, and politics, in order to include all of the perspectives necessary to design comprehensive solutions and achieve effective implementation of AI.

2.2.7 Summary

This review investigates the applications of AI across the economic infrastructure sectors of energy, water and wastewater, transport, and telecommunications. The main purposes to which AI has been applied are system provision, forecasting, routing, monitoring and security, and quality assessment and improvement. AI methods are increasing in popularity and capability, with deep learning and CNNs examples of recent developments in this field. The application of AI to infrastructure is also likely to continue to grow as infrastructure systems becoming increasingly instrumented and digitalised, providing data for AI tools.

Most of the existing research in infrastructure utilises machine learning methods, with other branches of AI explored less extensively. It is worth recognising that many applications of machine learning employ supervised learning and require access to some degree of historical data. The availability of such data may account for differences in research across sectors, with machine learning widely applied to forecasting of energy demand, but less so to water or transport demand. Although supervised learning methods dominate, unsupervised and reinforcement learning approaches have seen greater utilisation in more recent works, and the new field of deep learning has proven effective in instances concerned with large volumes of data.

Sensor networks are beginning to be recognised as a potential architecture for intelligent infrastructure systems through the Internet of Things. However, if they are to see widespread use, further research in knowledge representation will be needed. Ontologies and semantic approaches have been proposed, but rarely incorporated into larger artificially intelligent systems. As applied to self-healing systems, this reflects the need for consistent data formatting to ensure data can transfer between self-healing processes autonomously. With the growing availability of data from instrumented and digitalised infrastructure, if such data is appropriately handled, AI methods have the potential to contribute significantly to the development of the autonomous and anticipatory networks that a self-healing approach seeks to establish.

AI methods will have a valuable role to play in the burgeoning fields of distributed intelligence and the Internet of Things. This review of AI literature highlights the role of AI techniques in reasoning from data provided by sensor networks in the absence of human operators. This capability is crucial for the development of self-healing networks that can proactively detect and address issues or failures within the infrastructure systems. By leveraging AI algorithms, these networks can analyse the vast volumes of data generated by sensor networks and make informed decisions to optimise performance, improve resilience, and minimise disruptions.

This review acknowledges the existing research gaps, which are the limited incorporation of broader infrastructure targets in this body of research, the need for greater stakeholder engagement in developing solutions, a poor consideration of feasibility issues when developing technical solutions, and the lack of structured action-plans based on finding.

Nonetheless, this research provides a foundation for future investigations. It highlights the need to incorporate interconnected systems approaches in the problem formulation stage, paving the way for further research on self-healing infrastructure systems.

2.2.8 Further work

This work is limited in scope to economic infrastructures. Further work could broaden this definition of infrastructure to explore the use of AI in, for example, solid waste, finance, agriculture and food networks, or in social infrastructures such as healthcare, education, arts and culture. This work also identifies limited research at the intersections of different infrastructure sectors, something which could be further explored in future work.

The criteria identified as having limited coverage in Table 7 would benefit from greater consideration in future research. For example, having identified a gap in literature regarding action-orientated approaches, future work could seek to bring together the findings of research already covered in this review to suggest areas where it can inform action plans and guide policy. This could look to bridge the gap between research in this field and the governance of infrastructure systems. Similarly, this research recognises that, while technical developments in AI have led to significant improvements in the accuracy of solutions, there remains a lack of focus on the feasibility of potential interventions. Future work may wish to explore the possibilities and limitations of AI in infrastructure systems through this lens, perhaps by exploring the financial, technical, and regulatory requirements of implementing AI-based techniques in different geographies and economies.

3 DATA DESCRIPTION AND PREPARATION

3.1 DATA DESCRIPTION

3.1.1 STUDY SCALE

The developed case study chosen for this thesis focuses on the issue of leakage management. The data provided for this study is at the district metered area (DMA) level. The concept of the DMA was introduced in the 1980s in the UK, where the use of DMAs is now standard practice for water companies. A DMA is a section of the water distribution network that is hydraulically isolated. Sensors are typically installed at the input and output of the DMA so that demand in the area can be monitored by the flow through these sensors. DMAs can contain both residential properties and commercial buildings, and range in size from a dozen properties up to several thousand properties. A diagram illustrating how water systems are divided into DMAs is shown in Figure 12.

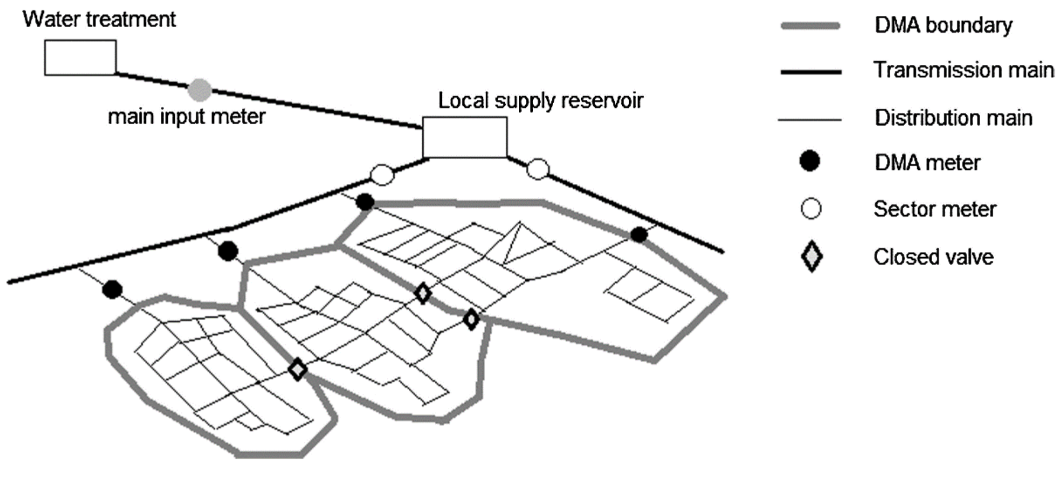


FIGURE 12: TYPICAL CONFIGURATION OF DMAS IN A WATER DISTRIBUTION SYSTEM. SOURCE: [480].

3.1.2 LEAKAGE MANAGEMENT

Breaking the larger, more complex water distribution network down into smaller DMAs primarily serves as a tool for improved leakage management, but additional benefits include the potential to isolate districts in order to protect the wider network during accidental or malicious contamination events and the ability to introduce a different water supply source for a given DMA to better control water quality [481]. While leakage management at the DMA level allows for a much more focused response, additional data is required if a particular burst is to be attributed to a specific pipe. This may be in the form of additional data on pipe properties or further flow or pressure data from targeted temporary sensors or from investigations on-site by an exploratory team dispatched by the water company (as is current standard practice). This study, therefore, is limited to the management of leakage at the DMA level, with the work of identifying the specific leakage site left to the teams that the water company would send out to the DMA identified as being impacted by leakage. There is potential for improving this method to include burst localisation, should sufficient additional data be available.

Data for the case study presented in section 4 is provided by a large UK water company, responsible for the supply and distribution of water to over 5 million households in the UK. Some data is made available publicly by the company via an open data collaborative, while other data is shared for research purposes under a data sharing agreement. Discussions with the data team at the company provide additional insight, based on their knowledge of operating practice, that is of use to this study. Data provided includes water flow data, at 15-minute intervals, for over 2,000 district metered areas (DMAs) managed by the company, covering a time period of one year, as well as a repair log covering the same DMAs.

This study uses a water flow dataset of 2,173 DMAs. The DMAs represented in this dataset range in size from 13 properties (consisting of 7 ‘household’ properties and 6 ‘non-household’ properties) to 5,167 properties (consisting of 5004 ‘household’ properties and 163 ‘non-household’ properties). Figure 13 shows the distribution of DMA property numbers for this dataset. This distribution shows a tailing off above 1,500 properties, with very few DMAs containing a total of over 3,000 properties. Analysis of the property types finds that, for over 90% of DMAs in this dataset, 'non-household' properties make up less than 20% of the total properties within the DMA. While a detailed exploration of how the property characteristics of a DMA impact leakage is beyond the scope of this study, it is worth noting that the ratio of 'household' to 'non-household' properties in a DMA may well affect typical flow patterns within the DMA. The potential implications of this are addressed in section 5. However, that so many of the DMAs within the dataset provided contain relatively few 'non-household properties' suggests that flow behaviour is likely to be similar across much of the dataset (albeit varying in magnitude due to the different property totals for each DMA), and thus any given method of leakage detection via analysis of flow data is likely to perform consistently across much of the dataset.

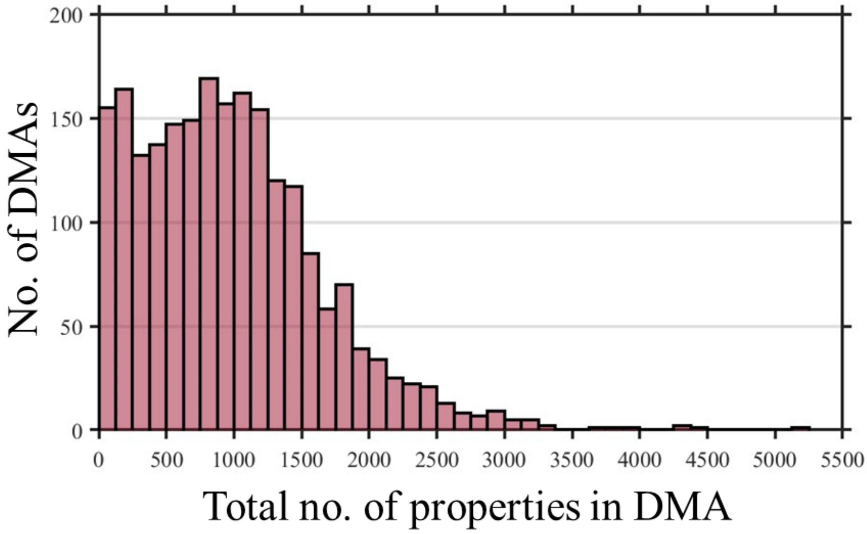


FIGURE 13: DISTRIBUTION OF TOTAL NUMBERS OF PROPERTIES PER DMA FOR ALL DMAS.

3.1.3 FLOW AND REPAIR MANAGEMENT

The flow and repair data were originally provided by the water company in csv format, with an example of the flow data shown in Figure 14a. The dataset consists of water net flow (in litres/second) for each DMA recorded at a 15-minute interval from April 2016 to April 2017 (~ 365 days × 24 hours × 60 minutes/15-minute interval = 35,040 data points).

Each data point is given a validity code based on the water company's assessment of the sensors' records. These codes – 'V' for valid, 'I' for invalid, or 'M' for missing – reflect any possible breaks or faults in the sensor readings. Invalid or missing sections represent less than 5% of all DMA flow data.

	A	B	C	D	E
1	DMA	Date	Time	Flow	Flow Validity Code
2	5	01/04/2016	00:00:00	2.667	V
3	5	01/04/2016	00:15:00	2.678	V
4	5	01/04/2016	00:30:00	2.689	V
5	5	01/04/2016	00:45:00	2.656	V
6	5	01/04/2016	01:00:00	2.722	V
7	5	01/04/2016	01:15:00	2.678	V
8	5	01/04/2016	01:30:00	2.6	V

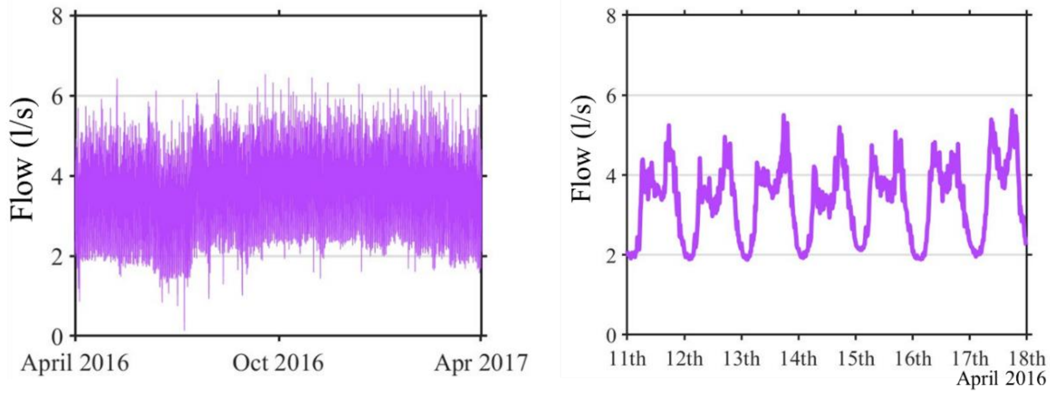
(A)

	A	B
1	DMA	Date
2	1	13/07/2016
3	1	30/01/2017
4	1	30/01/2017
5	5	08/10/2016
6	5	14/12/2016
7	5	09/01/2017
8	7	30/07/2016

(B)

Figure 14: Examples of unprocessed (a) flow data and (b) repair data

Figure 15a shows a full year of flow data for one exemplar DMA. The magnitude of flow remains broadly consistent throughout the year, with some seasonal fluctuations and some spikes of large flow rates. Figure 15b shows a standard week of valid flow data from the same DMA. The figure shows the typical volatility over a 24-hour period of flow data; minimums are seen during the night hours, with peaks occurring during the morning and late afternoon that correspond with a large proportion of the population leaving for and returning from work/school. This is consistent with patterns seen for many types of human-based behavioural or demand-based data.



(A) (B)

FIGURE 15: FLOW DATA FROM DMA 5 FOR (A) A FULL YEAR AND (B) A TYPICAL WEEK.

The provided dataset also contains the repair logs during the one-year period with corresponding repair dates for respective DMAs (although the exact timestamps of repairs are unknown). An exert from the repair log provided by the water company is shown in Figure 14b. In total, the logs contain the dates of over 5,000 recorded repairs across 1,646 unique DMAs. Although this repair log does not explain each repair's reasons, it is assumed that the entries are mainly due to leakage/burst events (based on discussions and additional data provided by the water company). Repairs are typically prompted either by customer leakage reports or the identification of unusual flow data by water company operators. If a leak is customer-reported and visible at the surface level, it is often repaired within a few hours or days. However, leakages that are not evident (those that do not result in visible water at surface level in an area where this would be noticed by residents) may take several weeks to repair. This delay between the onset of the leakage/burst event and the repair date means that a direct comparison of flow and repair logs is insufficient to tag the leakage dates in the dataset. Instead, it is necessary to utilise a method that identifies 'abnormal' flow data representing probable leakages/bursts. The timing of this flow can then be compared to recorded repair logs to ensure that the identified bursts are within the vicinity of the closest logged repair date (after the burst). In the absence of widespread metering, it is assumed that repair logs are the best alternative for the verification of identifying leakage events. This is verified in the pre-processing stage through comparison of anomalous flow with recorded repair dates.

3.2 DATA PREPARATION

As the case study involves historical data from a real-world system, there are several steps involved in preparing data for modelling components of the frameworks and ensuring data can flow between frameworks. Figure 16 illustrates these steps in a methodological framework. While the case study offers examples of specific models or methods for each of the self-healing processes, these are not intended to be prescriptive and there is the possibility to substitute models/methods based on specific operational needs.

The pre-processing element of data preparation can thus be separated into pre-processing of the dataset for the task of leakage management and pre-processing specific to the models chosen for the case study. The former involves data cleaning and completion, as well as identifying and formatting leakage data (and non-leakage data) in order to facilitate the task of leakage management. These steps are relevant not only to the specific data provided for this study but would need to be applied to any dataset intended for the proposed frameworks for leakage management. This process is covered in section 3.3.

The next step of data preparation is pre-processing specific to the models chosen for the case study. As an example, in this case study, machine learning models are chosen that require a fixed number of inputs, and so data needs to be formatted to ensure consistency in input size across flow data training samples. If the self-healing processes are to be adapted for real-world implementation, these steps may need to be modified or removed depending on what models are chosen by operators. The pre-processing necessary for the models chosen for this case study is detailed in section 3.4.2.

Once data has been sufficiently prepared, it can be input into the models and methods detailed in frameworks for each self-healing process. These frameworks are described in detail in chapter four.

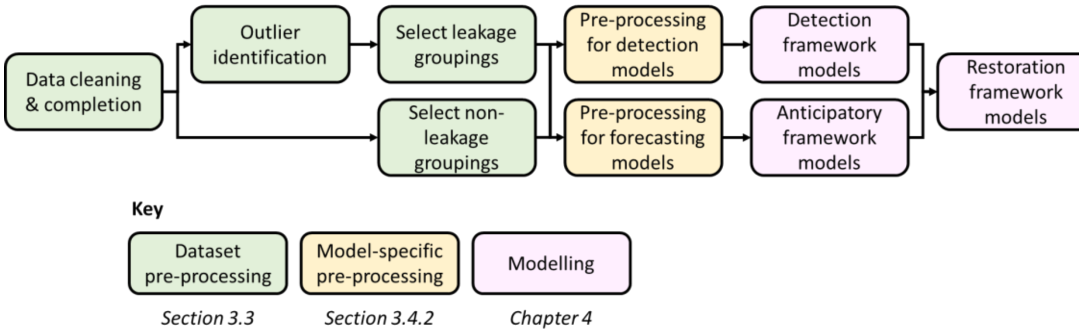


FIGURE 16: METHODOLOGICAL FRAMEWORK.

The remainder of this chapter details how the dataset described in section 3.1 is prepared to train and test the frameworks for self-healing processes. Section 4.1 covers the development of these frameworks and details of their components, and the results of testing these frameworks on the dataset are presented in section 4.2. The findings of this case study and their implications are then discussed in section 5.3.

3.3 DATA PRE-PROCESSING

Ideally, the proposed frameworks would be trained on a dataset of confirmed leakages (as well as confirmed non-leakage flow) drawn from a complete dataset without any missing or invalid water flow data. However, an ideal dataset is unrealistic due to the various aberrations and data errors in real time. Hence, it is necessary to complete the available water flow data statistically and to select appropriate examples of water flow data to represent bursts/leakage events and periods of regular/non-leakage flow. This section outlines the pre-processing required to generate the inputs necessary to train the proposed frameworks.

3.3.1 Data completion

The raw sensor flow data can contain faulty segments labelled as “invalid” or “missing” or containing impossible flow values (such as negative flow) in the dataset. As this study proposes data-driven frameworks, ensuring the dataset is robust and doesn’t contain any invalid/missing data is vital. Hence, before utilising the dataset to develop the frameworks, the fault segments of the flow time series are corrected using Kalman smoothing [482], thereby ensuring that the frameworks are trained using a statistically robust dataset.

The need for pre-processing due to the prevalence of missing or erroneous data in water flow time series is a recognized issue [483], and several methods have been proposed for dealing with this issue, including filling missing data with preceding flow values [484] [485], but there is no singular method that is recognized as the standard in this field [486]. In order to rectify these issues in the flow data, this study uses Kalman smoothing to replace invalid data or complete the missing data [482]. Kalman smoothing is able to capture the time-varying behaviour present in dynamic models by updating the estimates based on new measurements and predictions. This allows for more accurate completion of missing data points, even when the system’s characteristics are evolving (e.g., changes in the physical properties of the water pipes due to ageing, corrosion, etc.). Kalman smoothing is also able to effectively handle missing data that follows an unpredictable pattern in terms of the frequency and length of missing sections (as is the case for the data used in this study) [487]. By smoothing the time series, not just completing the missing sections, Kalman smoothing reduces the impact of noise and outliers, helping to reveal underlying trends in the water flow data and thereby enhancing the data completeness. Thus Kalman smoothing is an ideal candidate model for handling missing or invalid time series data [488] [489].

Kalman smoothing is based on the technique of Kalman filtering (KF), a simple dynamic Bayesian network that uses observed measurements (assumed to be a combination of state and noise) to provide recursive estimates of the underlying state at each time-step t [490]. The KF process consists of: i) a prediction step, to estimate the underlying state and covariance, and ii) an update step, which uses information from the observed measurement (at time-step t) to revise these estimates [491]. Equations (1) and (2) are used in KF to represent the observation and the state of time-series data, where X_t is the observed (or measured) value at time-step t, y_t represents the underlying state, θ is a tuning parameter, and v_t and w_t are noise components that are assumed to be normally distributed with a mean of 0 and standard deviations of ϕ and τ, respectively.

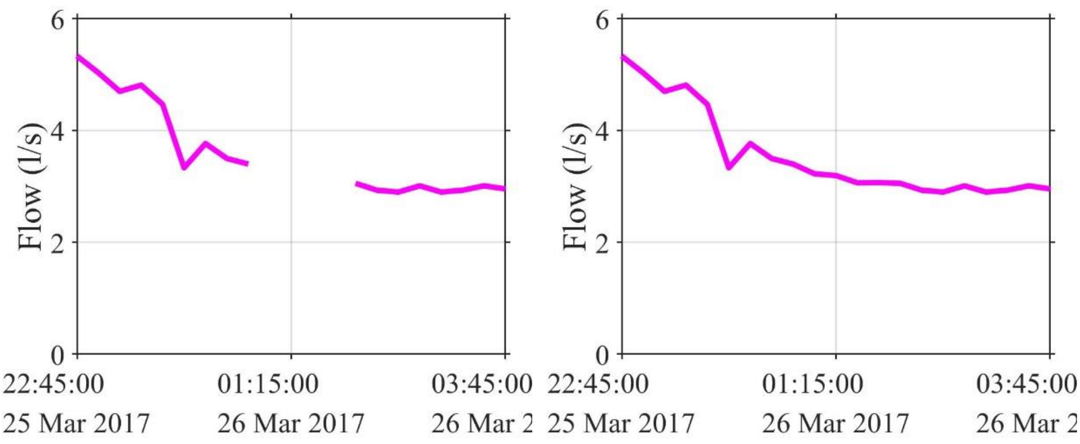
$$X_t = y_t + v_t(\sim N(0, \phi^2)) \tag{1}$$

$$y_t = \theta y_{t-1} + w_t(\sim N(0, \tau^2)) \tag{2}$$

Kalman smoothing is a post-processing method that estimates the state of time-series data before and after a given smoothing window and performs Bayesian-state interpolation of the observations. For a given window ($t = 1,2, \ldots, T$), a forward pass of the time series is completed with KF, followed by a backward recursive pass. This backward pass allows estimates to be refined using information from later observations after the smoothing window ($t > T$) [487], [492]. By incorporating both past and future observations, taking into account the uncertainty and noise present in the measurements, Kalman smoothing ensures that the completed data points are a good representation of the state and trends observed in the data, especially in the vicinity of the missing data [487].

A preliminary analysis of the initial dataset used in this study shows that ~95% of sections of missing or invalid flow data have under 480 datapoints (equivalent to 5 days compared to 1 year of total available water flow data), with over 85% of sections containing less than 96 datapoints (equivalent to 24 hours). The median and mode of the missing or invalid sections are observed to be 5 datapoints (equivalent to 75 minutes). Such a small ratio of missing/invalid data is not expected to affect the Kalman smoothing process. It should also be noted that from the total available flow data only ~10,000 randomly selected groupings representing leakage and non-leakage flow are used to train the frameworks, and so the impact of missing or invalid data is further restricted.

Kalman smoothing is used to replace all the faulty segments in the datasets. Figure 17 shows a short segment with missing flow data from an exemplar case (a) before and (b) after Kalman smoothing. The replaced section of flow, which was missing in this instance, smoothly connects the preceding and subsequent data, producing a flow profile that follows the expected pattern for this section. The fluctuation from the overall flow curve is no more than is seen is the observed adjacent data. Thus, Kalman smoothing can replace erroneous sensor data with realistic values based on the available non-erroneous data. This allows complete flow data to be provided to the leakage prediction and identification models and ensures that the anomaly detection stage of the frameworks target leakage rather than erroneous data. This process is repeated for all faulty segments of the dataset individually.



(A) (B)

FIGURE 17: SECTION OF MISSING DATA (A) BEFORE AND (B) AFTER KALMAN SMOOTHING, DMA 586

3.3.2 OUTLIER LABELLING

Ideally, flow data during known leakage events would be flagged as such in the dataset provided. However, bursts in real networks are rarely so neatly catalogued, with most leakage events being identified in the aftermath through customer reporting. Therefore, the best available verification for leakages in the available dataset is assumed to be the recorded repair log. However, the repair logs do not correspond to the leakage timestamps (rather only contain repair dates), and the actual timestamps of leakages are unknown. Hence, it becomes necessary to use post-hoc algorithms such as anomaly/outlier detection methods to statistically label the most probable leakage timestamps [493] [494]. In this study, leakage events are treated as outliers and are identified using a tree-based unsupervised machine learning algorithm: isolation forest [495]. Isolation forest assumes that outliers will be rarer than expected datapoints and have different attributes, making the outliers easier to isolate. In terms of decision trees, this places outliers closer to the root node than the normal data points. The classification threshold, which separates outliers from non-outliers, is set by a hyperparameter called contamination fraction [496]. In this study, a contamination fraction of 0.005 is selected. This algorithm is used to label the flow data for the network, which is comprised of over 2,000 district metered areas (DMAs), as outliers and non-outliers, and the outliers are further analysed to validate the indication of potential leakages.

It is important to acknowledge that leakages that occur gradually and remain undetected for an extended period may not have a corresponding repair log and might not be identified as an outlier, especially if the leakage began before April 2016 (the start of the study period). Consequently, the outliers selected to train the frameworks are more likely to represent new bursts or leakage events rather than background leakage. If data on background leakage were to become available, the framework could be trained using relevant examples. However, such data is not accessible for the current study. Nevertheless, the analysis of Z values, as presented in the results section of the case study (section 4.2), confirms that the points selected during the data pre-processing stage indeed represent genuine outliers.

Figure 18 presents the outliers detected in the flow data of the most-repaired DMA. The dashed lines in the figure show the dates of repair based on the repair log, while the green circles are the outliers flagged by the isolation forest. It can be observed that the isolation forest algorithm performs well in identifying both extreme outliers and extended periods of unusual flow rates. The detected outliers, particularly extreme ones, correlate well with repair dates. While a few repair dates are observed to be away from the outlier data, this can be due to the repairs being conducted for reasons other than pipe leakage, such as replacing aging infrastructure or capacity upgrades, which are not of interest in this study. It is further observed that the algorithm also flags some other unusual flow data points that do not appear to be leakages as they aren't close to the repair dates. Hence, it is crucial to identify outlier groups so that only extended periods of irregular flow are flagged as outliers hence leakages, while isolated individual outliers are discarded. For this reason, leakage groupings labelled LKG are required to be a minimum of 20 outliers in length, which represents five hours of water flow. The literature supports this approach, suggesting that abnormal flow shorter than a few hours in size is likely not leakage but sensor error, firefighting, or an industrial event [493].

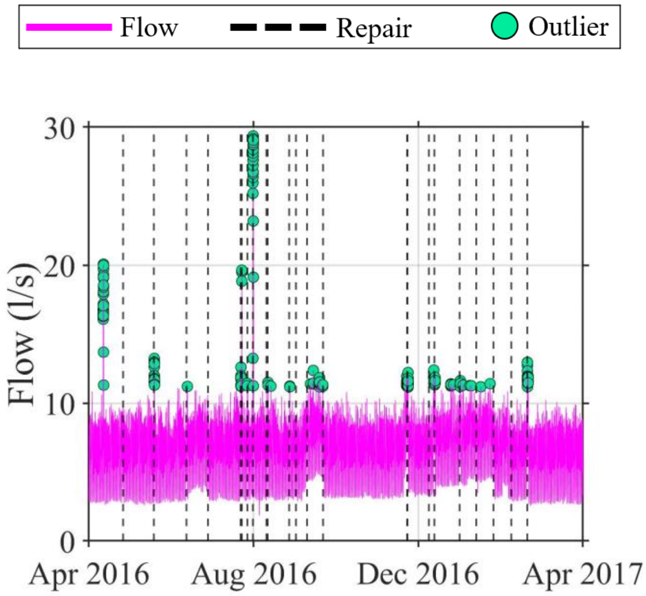


FIGURE 18: OUTLIER IDENTIFICATION AND REPAIR DATES FOR DMA 586

Identifying accurate leakage data points is essential in developing a reliable tool for classifying leakage and non-leakage data. To validate the assumption that the detected outliers can act as a reliable proxy for the true leakage events, the timesteps at which the outliers are flagged using the algorithm are compared to the repair dates in the repair log. Though these timings are not expected to align perfectly due to fluctuations in the time taken to respond to suspected leakage, a reasonable time frame is necessary (a time frame of 30 days is used here). Furthermore, it should be noted that the repair logs only contain the repair dates (rather than exact timestamps); hence time lags are expected.

Figure 19 shows the time difference between each repair date (assumed to be 23:59:59 hrs of each repair date) and the closest outliers before and after the repair dates for DMA 586. The DMA has undergone 23 repairs (shown on the *y*-axis) during the year. As the repair logs contain only the date of repair, and not the time, this analysis assumed that each repair occurred at 23:59:59 hrs; hence the outliers occurring on the same date as a repair are recorded to occur prior to the repair. Based on Figure 19, it is noted that the outliers correspond well with documented repairs, with many repairs occurring within two to three days of an outlier, which are likely to represent repairs to customer-reported, surface-visible bursts. All but six of the recorded repairs in the example shown in Figure 19 took place less than six days after a record of outlier flow. This falls well within the repair timescale that would be expected for less urgent, non-visible leakage or leakage on land requiring permissions for access. Those that fall over ten days from an outlier may represent leakage in a rural or low-residential area, which may have gone unnoticed for a while, or simply reflect less-urgent leakage that was lower priority during a busy period of repairs. No repair to this DMA occurred greater than 17 days after an outlier, which suggests that it is reasonable to assume a significant majority of repairs correspond to leakage/bursts. These findings confirm that repair data is the best proxy for leakages/bursts.

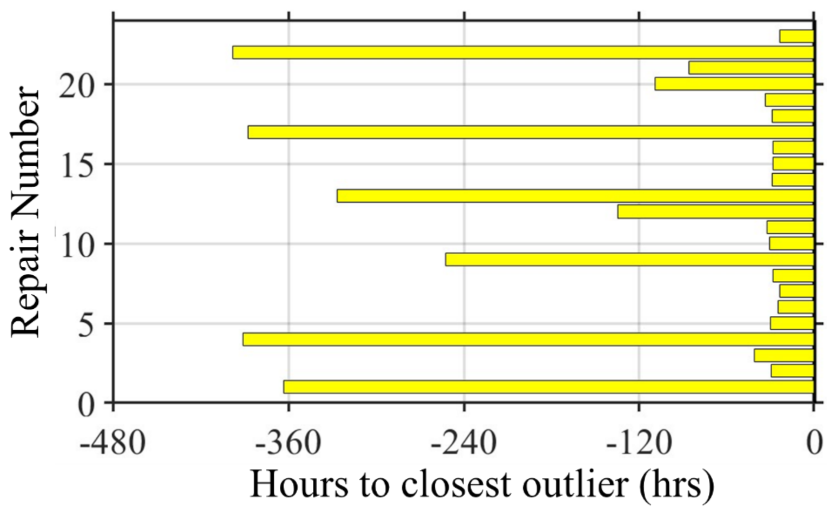


FIGURE 19: TIME DIFFERENCE BETWEEN REPAIRS AND CLOSEST OUTLIERS (HRS) FOR DMA 586

Accurate identification of leakage can allow water companies to react effectively to minimise water losses and ensure supply continuation. In this study, the data from identified leakage is also used to train leakage prediction models. This can facilitate the anticipation of leakage and prioritisation of preventative maintenance.

3.4 MODELLING

3.4.1 INTRODUCTION

This section details the additional decisions taken to select and prepare the training and test datasets for the AI-based models used the in the case study. The models themselves, and the frameworks in which these models are components, are described in greater detail in section 4. To ensure that the models and frameworks, while able to stand as individual processes, can come together to form a comprehensive self-healing approach, inputs and outputs are compatible across the suite of frameworks.

3.4.2 SELECTION OF TRAINING AND TESTING DATASETS

3.4.2.1 Introduction

The outlier data provided by the isolation forest algorithm is further processed to ensure it is in a suitable format for training the data-driven frameworks. Once the outliers have been identified and examined, they must be grouped into leakage/burst (LKG) and non-leakage/usual-flow (NLKG) groupings to provide training samples for the components of the modelling frameworks. The outliers close to each other in time (within a few hours of each other) are likely to indicate a single burst rather than multiple distinct bursts and hence are grouped together. Single outlier points may indicate sensor error or data quality issues. In addition, the literature indicates that short periods of anomalous flow, lasting just a few hours, can often be attributed to industrial or firefighting events rather than leakage [493]. Hence, a minimum length of outlier grouping is required to ensure that outlier groupings selected for training the frameworks are likely represent leakage. For this study, a minimum length of five hours of flow data (20 datapoints) with outliers is qualified as LKG groupings. Based on this criterion, ~3,500 LKG groupings are identified for all DMAs combined, ranging from five hours to ~3.5 days of outliers.

As a crucial element of the self-healing process is differentiating between leakage and regular flow data, it is necessary to include similar examples of non-leakage groups (denoted as NLKG) where the output corresponds to the data labelled as non-outlier. However, as the NLKG groups are more prevalent in the dataset than the number of LKG groupings, all the NLKG groupings cannot be used to train the proposed framework. This is due to the data-driven nature of the models used, and the significant difference in the sample sizes of the two groupings can cause considerable bias in tuning the models. Hence, random samples of NLKG groupings are obtained from the ~2,000 DMA flow datasets with different sampling ratios between the NLKG and LKG groupings. Based on the performance of the models (discussed in section 4), a sample size with NLKG samples equivalent to two times the number of LKG samples is used for further study.

3.4.2.2 Anticipatory process

For the anticipatory framework, as the LKG flow data is expected to be forecasted from the final trained framework, preceding flow data is needed to be used as the inputs. To have sufficient data for training, this input data needs to be equal to or greater than the LKG data in length. Any LKG groupings where the input data does not meet this requirement are discarded. The maximum length of input data is set to 672 data points, representing a week's flow data. This is deemed sufficiently long to give a representative sample of flow before an outlier. A total of 3,409 LKG groupings are selected with these criteria. As the model is ANN-based, it requires a set number of input and output data points. This means that the length of LKG groupings and the preceding input data must be the same for all examples. The maximum length of LKG data is observed to be 335 points. Hence all inputs need to have 672 data points, and the outputs need to be 335 in length. This consistency is obtained by zero-padding, where zeros are added before the flow data for inputs and after the flow data for outputs (i.e., LKG data). This process prepares the leakage dataset. An example of LKG grouping is provided in Figure 20a. An example of NLKG grouping is shown in Figure 20b. While the input data for both examples exhibit very similar behaviour, the LKG grouping has a significantly higher peak of output flow. The output flow for the NLKG grouping, in contrast, shows no noticeable difference in behaviour relative to the corresponding input data.

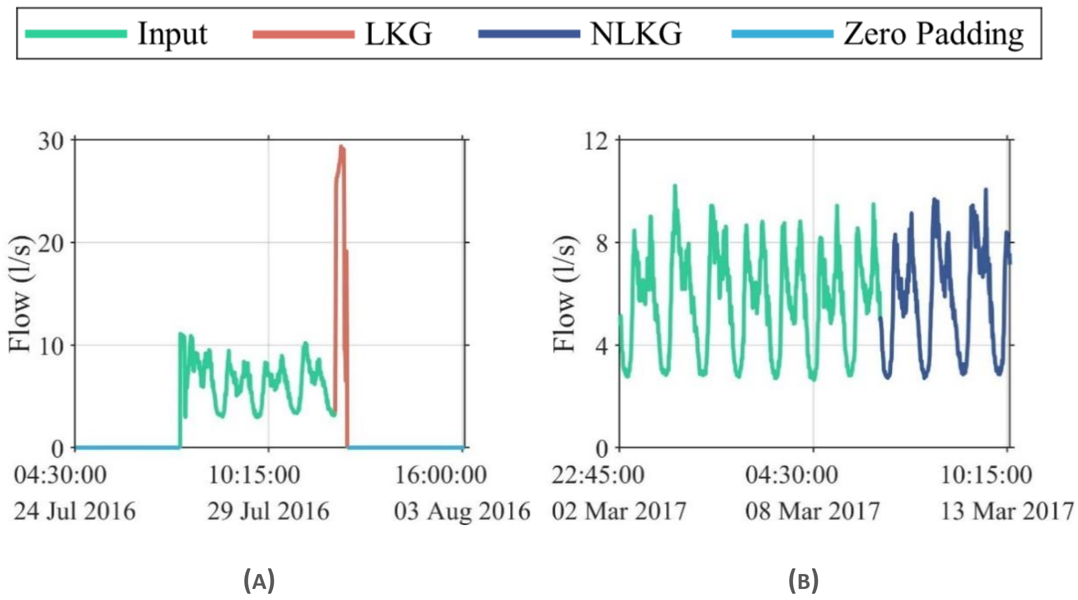


FIGURE 20: EXAMPLES OF GROUPINGS FOR (A) LKG DATA: DMA 586 OUTLIER 1, (B) RANDOMLY SELECTED NLKG DATA: DMA 586 GROUP 1

Variance checks are performed for both LKG and NLKG groupings, and any LKG group with a coefficient of variation (COV) below 0.1 or greater than 10 for the input section of data is discarded. Furthermore, for NLKG groupings, both the input and the output section of the flow data is required to have a COV between 0.1 and 10. This is done to ensure that the selected non-outlier information is error-free and doesn't contain any non-detected peaks or portions of unbalanced flow (any unexpected/unlabelled malfunctioning). In total, ~10,000 LKG and NLKG groupings are used as the final dataset, with 672 points of input and 335 points of output for each grouping. This dataset is then used to train and test a hybrid forecasting model for leakage prediction.

3.4.2.3 Detection process

The detection framework, which is variational autoencoder (VAE) and SVM-based, uses the same initial selection of LKG and NLKG groupings. Figure 21 shows the distribution in the length of the LKG groupings. It is observed that outliers have a large range of lengths, though shorter outliers of five to ten hours are far more common. Indeed, over 80% of outlier groupings contain less than 12 hours, or 48 points, of flow data, and over 90% of outlier groupings contain less than 24 hours, or 96 points, of flow data.

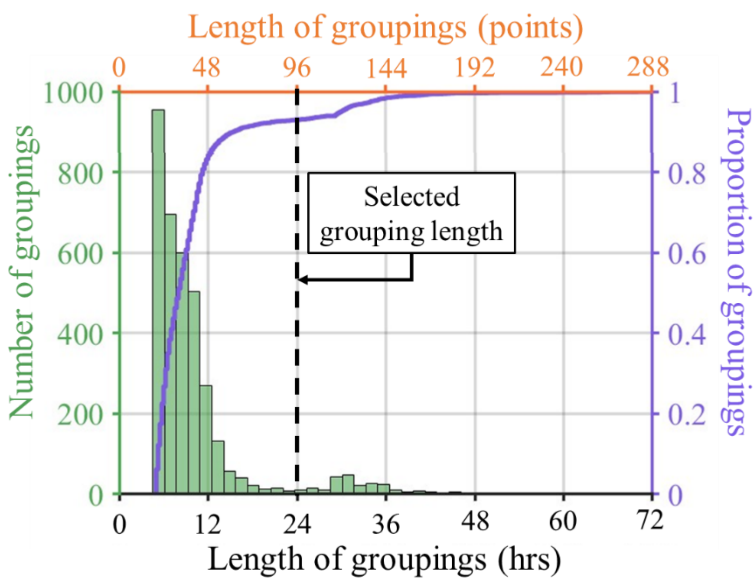
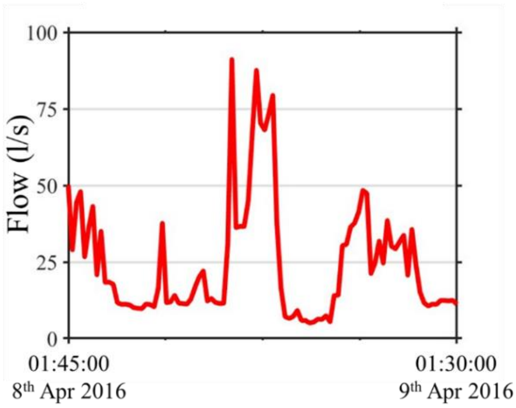


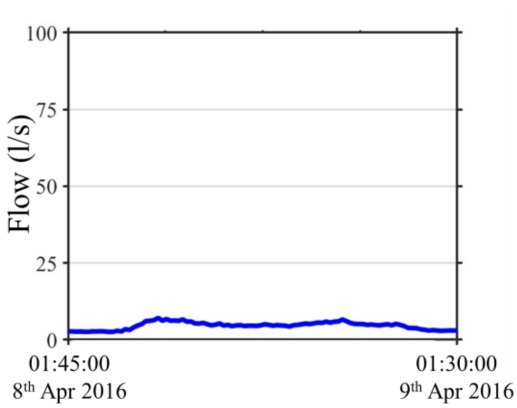
FIGURE 21: LENGTH (IN HOURS AND NUMBER OF DATA POINTS) OF LKG GROUPINGS

As for the RNN-based framework for leakage prediction, the VAE requires all input sequences to have the same length. Hence, LKG groupings are again padded with zeros (after the flow data) to make them up to the length of the largest grouping. However, in order to limit the impact of the zero-padding on the training of the VAE, a maximum limit of LKG grouping length is set. Various cut-offs are tested, and 96 datapoints, corresponding to 24 hours of flow data, is chosen for this study. It is evident from Figure 21 that over 90% of LKG groupings contain less than 24 hours of data, and hence this cut-off achieves the compromise of retaining a representative sample of LKG groupings while restricting the impact of zero-padding on the training of the VAE. Around 3,500 potential LKG groupings are thus identified.

As in the above section, to ensure that the input data does not contain any erroneous data points, variance checks are performed on the NLKG groupings. These checks lead to a final dataset of 3,336 LKG groupings and 6,818 NLKG groupings. This results in a total of ~10,000 flow times series LKG and NLKG groupings for training the proposed detection framework. Figure 22 shows an example of an (a) LKG and (b) NLKG grouping, for input into the VAE. It can be observed that the LKG example has significantly more variability (with flow values ranging from below 10 l/s to over 80 l/s), while the NLKG example exhibits much less fluctuation (remaining below 10 l/s throughout the 24-hour period). The peak flow of the LKG example is also over eight times greater than the peak flow of the NLKG example. This contrast in flow behaviour is common between LKG and NLKG groupings, with LKG groupings typically having higher maximum flow values and greater variability in flow values.



(A)



(B)

FIGURE 22: EXAMPLES OF (A) LKG AND (B) NLKG GROUPINGS FOR TRAINING THE PROPOSED FRAMEWORK

3.4.2.4 Restoration process

As the restoration process uses the outputs of the anticipatory and detection processes in order to produce a prioritised schedule of repairs, very little additional data pre-processing is required. Outputs of the two processes are given a code to indicate whether they are forecasted leakage or detected leakage, as the two are combined for the scheduling stage.

3.4.3 MODEL SELECTION

Selection of the AI models is done based on a thorough review of literature in the relevant fields, as well as a review of AI methods for cross-cutting purposes (e.g. forecasting). Literature is therefore not limited to the water sector but considers time series modelling for a variety of failure events. The type of available data is also considered, to ensure that methods are selected that are appropriate to the quality and quantity of the dataset provided. Once model families are identified, different variations of modelling approach are explored (for example, coupled and un-coupled approaches are explored where appropriate). Finally, the details of each model are refined through tuning and hyperparameter optimisation. Section 4 presents the architecture of chosen models in detail.

4 CASE STUDY: A SELF-HEALING APPROACH TO LEAKAGE MANAGEMENT

4.1 FRAMEWORKS

This section describes the development and training of frameworks for the anticipatory, detection, and restoration processes for this case study of leakage management as a self-healing system. Frameworks for each process are explained individually but with wider system integration in mind. Each process is trained using the same dataset described above and outputs of the anticipatory and detection processes are used as inputs for the restoration process, illustrating how the frameworks act in combination to deliver comprehensive leakage management at a system level.

4.1.1 Anticipatory Process

4.1.1.1 Background

A critical domain in the field of leakage management is the forecasting or prediction of leakage. Unlike leakage detection, which is concerned with the identification of bursts from flow data after they have occurred, leakage prediction/forecasting aims to anticipate anomalous flow before it occurs, thereby enabling early warning of potential leakage within a given forecasting period. This allows preventative maintenance to be scheduled, which can act to repair pipes before any water is lost as leakage. While the field of leakage detection has observed several dedicated studies, leakage prediction/forecasting has received significantly less attention from the research community due to its complexity. Leakage forecasting at a regional level has been conducted over various time periods ranging from weeks to a year. For example, Birek et al. [497] utilize an evolving fuzzy algorithm on historical leakage levels and repair data across nine regions consisting of aggregated DMA areas to forecast the future rates of monthly leakage. Studies on leakage forecasting at the individual pipe level have analysed pipe properties, such as diameter, age, and material, as well as other factors, including soil type, ground movement, and traffic loading, to assess their impact on leakage likelihood [498] [499] [500].

In recent years, the forecasting of water flow data at a DMA level has gained attention [501] [502]. Typically, these studies have primarily focused on predicting regular water demand rather than specifically addressing leakage prediction [53] [503]. Water demand forecasting aims to estimate expected water usage, and thus it mainly focuses on forecasting typical non-leakage flow. On the other hand, leakage prediction requires forecasting anomalous flow, which can indicate potential leakage incidents [504]. While water demand forecasting is valuable for resource planning, leakage prediction can significantly improve asset repair strategies and enhance system efficiency by reducing water loss [505].

However, there have been some studies that attempt to detect leakage by forecasting expected non-leakage flow levels using Bayesian forecasting methods [501] [504]. These studies compare the forecasted flow levels with incoming flow data, and a significant difference is considered indicative of leakage [501] [504]. It has been suggested that machine learning techniques, particularly artificial neural networks ANNs, have the potential to outperform baseline methods in forecasting flow data at the DMA level [502]. Recent research has indicated that LSTM-based neural networks offer superior performance in demand forecasting, surpassing other time series forecasting models in predicting typical short-term water demand in a single DMA case study [503]. Recent work on the forecasting of time series climate data suggests that using an information theory based loss function [506] can improve performance over the traditional loss functions seen to date in water demand forecasting [503].

Hybrid forecasting methods, which combine various forecasting techniques with error (residual) forecasting modelling, have shown high levels of accuracy and the ability to forecast time series with different characteristics [507]. Applying these methods to the water sector has clear benefits, and some studies have already applied hybrid methods to typical water demand forecasting [508] [53]. The effectiveness of residual forecasting in improving time series forecasting of water demand has been demonstrated at both regional [509] and DMA levels [510], with the KF being the preferred method for residual forecasting in these studies. However, it should be noted that these studies have focused solely on demand forecasting and do not address the forecasting of leakage flow [509] [510]. Furthermore, the LSTM-based forecasting method [503] and the residual forecasting approach with KF [510] have so far been applied only at the scale of a single DMA and have not been combined or applied to large datasets, such as the thousands of DMAs managed by each water company [503] [510]. Therefore, there is a need to explore the potential of combining these methods and applying them to a large dataset to harness their benefits on a broader scale (such as the thousands of DMAs managed by each water company).

Although there is clearly significant potential in this area, there has not yet been a study that uses real sensor data and sophisticated data-driven machine-learning and deep-learning techniques to forecast, at any geographic level, the anomalous flow that indicates a burst. By forecasting anomalous flow, rather than contrasting a forecast of expected flow with incoming data, earlier warning can be provided for leakage, facilitating faster repair. An accurate forecast of leakage flow can also provide an estimate of expected water loss, which can inform the prioritisation of repair jobs. This places leakage forecasting within a bigger system of self-healing leakage management, which considers the processes of anticipation, detection, and repair [505].

4.1.1.2 Framework conceptualisation

As state-space models like KF are widely based on the assumption of stationary time-series, this assumption is validated in this study using an augmented Dickey-Fuller unit hypothesis test [511]. The test has the null hypothesis that the time series is non-stationary and has a unit root. For the flow data in this study, *p*-values are observed to be well below the significance level of 0,05, and the null hypothesis is rejected. This indicates that the flow data can be deemed stationary for state-space and other time-series modelling techniques.

Stationary time series typically consist of a combination of two components – trend and seasonal – and remaining noise [487]. Neural network-based models can have difficulty modelling seasonality directly from time-series data [512], and so additive time series decomposition is used to break down the time-series data into their trend and seasonal components, prior to input into the forecasting element of the framework [513].

Forecasting leakage allows more rapid leakage management than forecasting regular flow data and comparing this with incoming flow data to find leakage. The latter uses forecasting to facilitate leakage detection, while the former is a more proactive approach that seeks to anticipate leakage. Hybrid forecasting, using LSTM-based forecasting with an information theory based loss function and KF for residual forecasting, represents a combination of best-performing recent practice in the area of time series forecasting, with established accuracy in the area of water demand forecasting [503] [506] [507] [509] [510].

Figure 23 shows how incoming flow data is processed through the proposed framework and final estimates of flow are forecasted.

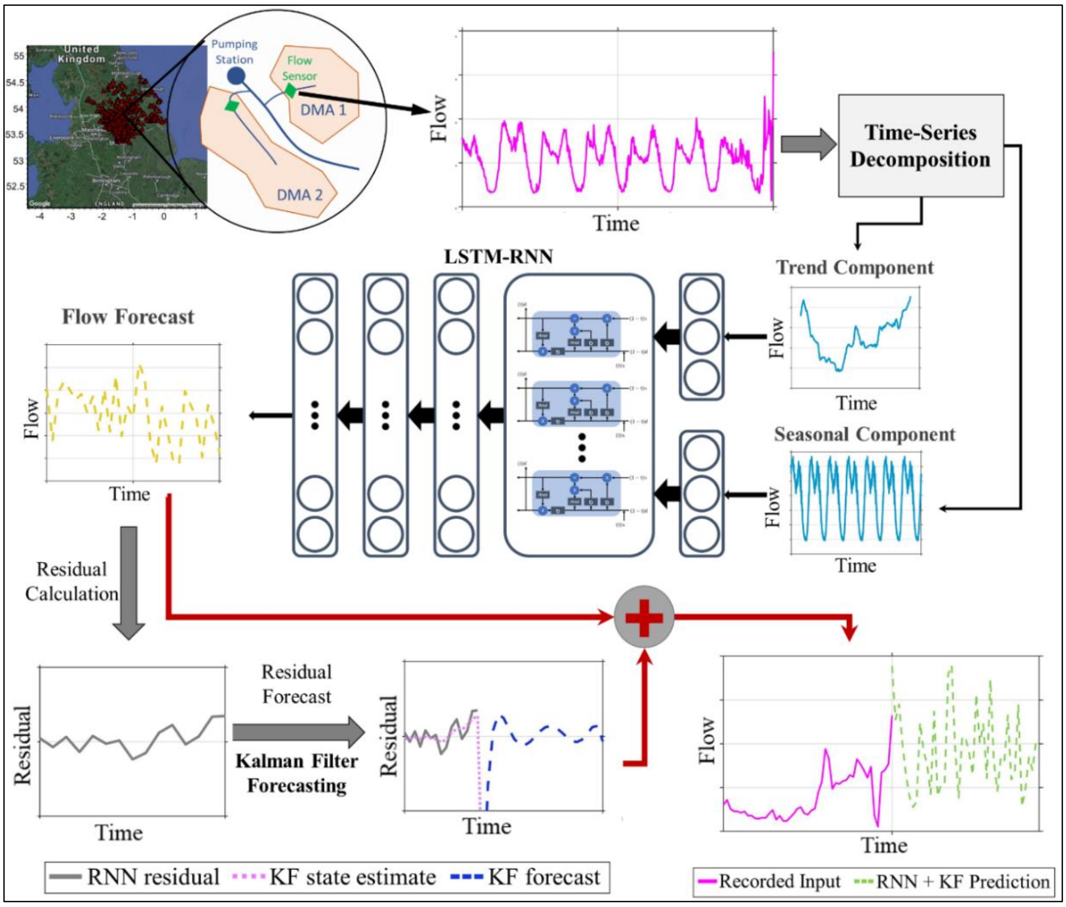


FIGURE 23: PROPOSED LSTM-RNN- AND KF-BASED FRAMEWORK FOR FLOW FORECASTING.

4.1.1.3 Training of the framework

The general procedure for training the proposed LSTM-RNN and KF-based framework is outlined here, then explored in greater detail in the following subsections. Having identified suitable examples of LKG/NLKG flow, a total of ~10,000 flow data series are prepared for training the proposed framework. Next, a time-series decomposition is conducted for each of the 10,000 selected flow data series to obtain its trend and seasonal components. These are then used as inputs to train an LSTM-RNN, which forecasts the mean flow data. The forecasted mean flow data is used to compute the residuals between the predictions and recorded flow values. The residuals are then further used to train a boosting KF that can use residuals in real-time to forecast the future residuals and further improve the predictions. Finally, the forecasted residuals are added to the mean forecast from the LSTM-RNN to obtain the final predictions. Hence, the two principal components of the trained framework are:

1) LSTM-RNN, which is trained to forecast the expected flow for $t + n$ points using $t - m$ recorded flow.
2) KF, which provides real-time estimates of residuals and hence shapes the expected predictions of LSTM-RNN closer towards to true flow.

A. LSTM-RNN

Effective forecasting of flow data can allow leakage to be anticipated, facilitating a more efficient approach to leakage management and system maintenance. In this study, the ANN-based model is used to forecast the mean flow for a future period of time. It is well known that a stationary time-series typically consists of two general components: i) trend and ii) seasonal [487]. The trend component represents the general pattern of the time-series data over the entire time duration. In contrast, the seasonal component refers to the cyclic repetition of a pattern within a specific time period. Neural networks can potentially struggle to model seasonality directly from time-series data [512]. Hence, to address this issue, additive time series decomposition is used to break down the input data of both LKG and NLKG groupings into trend and seasonal components, as well as the remaining noise [513]. In this case, the trend represents the general pattern of flow data over the input time window, while the seasonal component reflects the fluctuations in flow during 24 hours. Using the time-series decomposition of Equation (3), the input flow time series y_t is decomposed into trend, seasonal, and noise components, where T_t and S_t are the trend and seasonal components at timestep t, and ε is the noise in the data which is assumed to be normally distributed with a mean of 0 and a standard deviation of δ.

$$y_t = T_t + S_t + \varepsilon(\sim N(0, \delta^2)) \quad \textbf{(3)}$$

In this study, the decomposed trend and seasonal components are used as inputs to train an LSTM-RNN, which outputs the forecast of the NLKG/LKG flow of the groupings. RNNs are a class of ANN developed for modelling time-series data [514]. RNNs allow the outputs of a neural network layer at time-step $t - 1$ to be used as inputs for the same neural network layer for the following time-step t. This forms a directed graph and allows the transfer of 'memory' between adjacent time steps so that the output of the neural network layer at a given time step is dependent on prior elements within the time series.

Although RNNs can handle dependencies between individual steps in a time series, they suffer from issues with long-term dependencies and vanishing gradients [515]. As a result, RNNs struggle to learn if asked to use outputs from previous time steps (time lags) as inputs for estimating the current time step. Selecting an LSTM architecture for the RNN can solve these challenges. Each LSTM layer contains a set of recurrently connected blocks, with one or more recurrently-connected memory cells and three multiplicative gates regulating information flow [516]. The structure of an LSTM cell is presented in Figure 24. A cell state transfers relative information down the sequence chain and between LSTM blocks - the "memory" of the network. In each LSTM cell, a forget gate passes on information from previous outputs and the current input at time-step t and decides what data to keep in the cell state. An input gate decides how the current input should be used to update the cell state and modify the memory, and an output gate uses the input and the memory of the cell to decide the output for the current time step. Thus LSTM cells act as information processing units and provide a route for 'memory' to pass beyond adjacent cells, enabling the RNN to bridge long time lags steps [517], [518]. Hence in this study, LSTM-RNNs are used to develop the flow forecasting model.

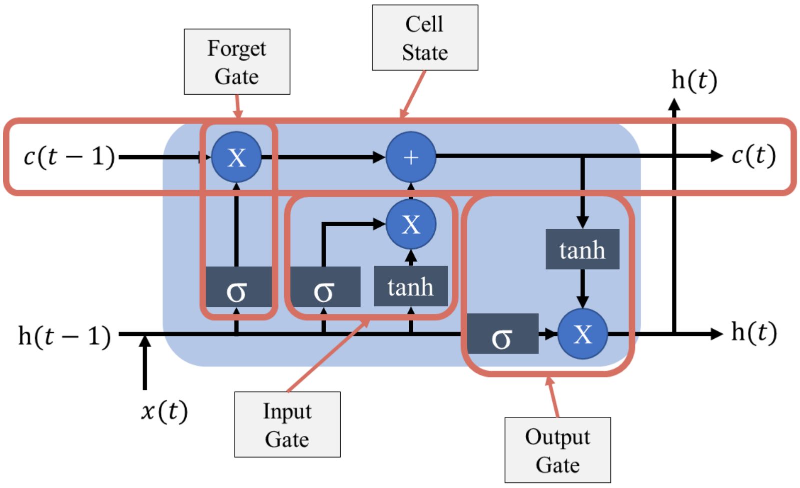


FIGURE 24: LSTM CELL STRUCTURE, WHERE c REPRESENTS THE CELL STATE, h REPRESENTS THE HIDDEN STATE AND x REPRESENTS THE INPUT.

The LKG and NLKG groupings are split into train and test sets such that 80% of both groupings are used in training and 20% of both groups are used for testing the LSTM-RNN. LSTM-RNNs of various configurations and hyperparameters are developed and trained. In particular, index of agreement (IA) [508] [509], described in Equation (4), is used as the loss function for training and testing the LSTM-RNN, where O is the recorded output data and P is the RNN predicted data, and n and i represent the total number of forecasted timesteps and the timestep of interest, respectively. A valuable tool for the comparison of model performance, IA gives a single bounded metric for pattern characterisation and comparison, yet also incorporates information on the magnitude of deviations into this metric and has therefore been widely applied to the assessment of model-produced estimates of time-series data [521].

$$IA = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|\ P_i - \bar{O}\ |\ + |\ O_i - \bar{O}\ |)^2} \quad (4)$$

The train set is used to develop the LSTM-RNN with several configurations and hyperparameters. The number of layers in the LSTM-RNN, the number of nodes in each layer, and the activation function are subject to tuning, with the IA of each configuration recorded for comparison. The training is conducted with 10% cross-validation. After hyperparameter tuning, the best-performing final LSTM-RNN architecture in terms of IA is shown in Figure 25. In particular, the LSTM-RNN network is trained using stochastic gradient descent [522] with Adam optimizer [523] and IA [508] [509] as the loss function. Since the values of IA range from 0 to 1, with 1 being the best match and 0 the worst match, the loss function is used negatively to allow gradient descent rather than ascent.

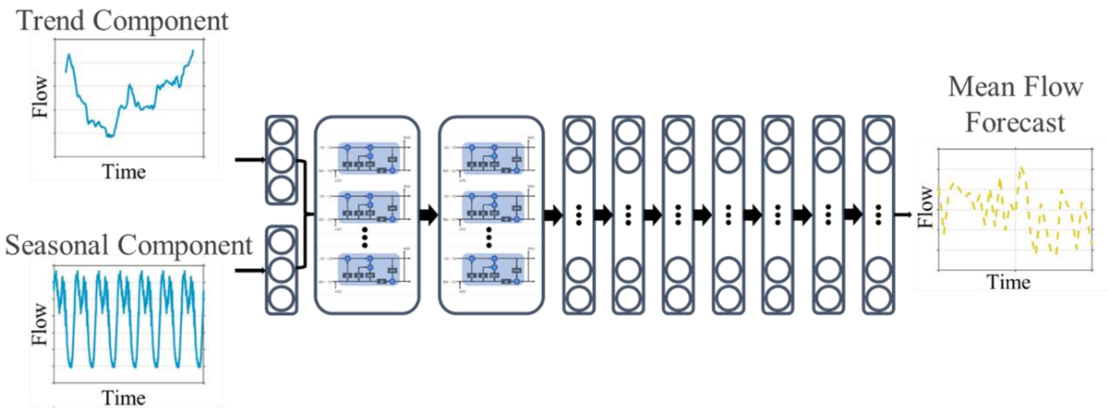


FIGURE 25: ARCHITECTURE OF THE TRAINED LSTM-RNN.

B. Kalman Filter

Since the LSTM-RNN is a pre-trained model, it cannot adjust to the fluctuations in real-time; hence, to further improve the predictions, a boosting concept [524] is utilised to model the early residuals observed between the LSTM-RNN-based flow forecast and real-time sensor recording of corresponding flow data. The early residuals are then used to estimate the future residuals for the uncertain time of the output length. Thus, modelling of residuals can improve overall forecast accuracy by providing an estimate of the error expected from the LSTM-RNN due to any real-time fluctuations. This study uses KF as the boosting model for forecasting the residuals in real-time [525]. The KF is a Bayesian method for sequentially estimating the states of a dynamic system where the state evolution and measurement models are linear and Gaussian [526]. The recursive nature of KF enables it to model continuously changing systems. KF also does not need to hold much memory and thus can be run very quickly, making it ideal for real-time applications [527]. In the residual forecasting model, the KF algorithm first uses Kalman smoothing to estimate the state of the observed residuals and then forecasts residuals for a pre-defined forecast period. Forecasting recursively uses the observation and state equations [528]. Given an initial estimate at time t, the KF first performs a prediction step, estimating the state at time $t+1$, as well as the uncertainty of this prediction. Once the observed value at $t+1$ is received, a correction step is performed. A calculation for Kalman gain adjusts the weights given to the incoming observations and current-state estimate. The prediction and uncertainty estimates are then updated based on this new information, and the cycle repeats for the next time step [491]. This continues for known observations at time-steps $t = 1,2, \dots, T$. Having provided the KF with sufficient known observations to tune parameters such as co-variance estimate and Kalman gain, the KF can be used to forecast a defined period of future time-steps ($t > T$) where observations are unknown. This process is repeated in real-time for complete predictions. As more recorded values are received, the KF model can update residual predictions to reflect this new information. The final flow forecast from the proposed framework is based on the addition of mean forecast from LSTM-RNN and residuals from KF.

4.1.2 Detection Process

4.1.2.1 Introduction

In the field of leakage management of water flow distribution networks, leakage detection is a critical research subject [529], [530], [531], [532], [533]. Sensor data can be fed into leakage detection models that seek to identify bursts by monitoring changes in the flow profile over a set window of time. Traditionally, the most common methods for identifying leaks utilise minimum night flow (MNF) [534]. This technique recognizes that water usage during night-time is less variable than in the daytime. Hence, the average nightly minimum over a specified window is used as a baseline for comparison with new flow data, with a significant variation (relative to a pre-defined threshold) indicating a leak [535] [493]. However, these techniques are not highly reliable as MNF methodologies have to deal with several uncertainties. Accurate use of MNF relies upon having sufficient knowledge to estimate several parameters, including active night users, leakage exponent (which varies with system pressure), and the hour-to-day factor [536]. Reliable estimation of these parameters typically requires both pressure and flow data. The selection of the best time window for the computation of MNF requires additional considerations and analysis. It has been shown that minimum error does not correspond with the selected night flow window but with the hour in which average demand applies [534]. While it is often the responsibility of trained operators to identify leakage from MNF, a significant proportion of leaks are reported to water companies by their customers [493].

Recent work has sought to improve upon traditional techniques, with new models using machine-learning methods to improve the accuracy and reliability of leakage detection [16] [17] [539]. Some of the machine-learning and deep-learning techniques utilised by these studies include ANNs [540] [532] [529] [541], SVMs [542] [543] [544],KFs [545] [546], and wavelet analysis [529]. With sufficient quality and quantity of training data, these methods have demonstrated strong performance in leakage identification [540]. Many of these models are trained using examples of standard flow data and flow during leakage bursts. The burst examples are typically obtained by matching the timestamps of abnormal flow patterns to pipe repair records or reports of visible leakage from consumers to water companies. Alternatively, the data can be simulated through a hydrant flush event that mimics a leakage burst [497]. Some studies do not use data from real water distribution networks and instead extract pressure data from simulation software-based network models [498].

Autoencoders (AE) are a relatively novel deep-learning technique that draws upon the concept of dimensionality reduction using ANNs with bottleneck shapes at the central layers of the ANN [548].VAEs are a type of AE that relies on Bayesian concepts and forces the bottleneck layers to possess a regularised standard normal space [547]. This reduces the dimensions of input data in such a way that the inputs similar to each other in terms of their characteristics lead to similarities in the outputs of the bottleneck layers [547]. Hence, within the setting of water leakage detection, it can be understood that with sufficient training of a VAE using leakage and non-leakage flow datasets, VAEs can be capable of differentiating between the flow classified as leakage or non-leakage. VAEs have demonstrated their potential in the detection of extreme events in numerous engineering contexts [549], including earthquake early-warning systems [550], detection of cyber-attacks [551], and structural health monitoring of infrastructure such as dams [552]. Various types of AE, including VAEs, have begun to be considered a tool for leakage detection in both water and oil/gas pipelines, where they have shown initial promise [106], [553]. However, studies using AE for leakage detection have relied on test-bed setups, where water flow behaviour can be strictly controlled. These setups vary in scale, from representing a single component [554] or a handful of pipes [555], to a broader distribution network more comparable in scale to a small DMA [106]. Some setups model only regular flow [555], while others simulate leakage events [106], [554]. Such setups allow for cutting-edge sensor technology to be used, and so all work to date has used hydroacoustic measurements from acoustic sensors [106], [554], [555] rather than traditional water flow measurements. While this can provide more accurate sensing, acoustic sensing is a less explored method of monitoring behaviour in water pipes. The technology has undergone limited deployment, and most DMAs are not subjected to acoustic monitoring. In developed nations with well-established water distribution systems, the cost of installing improved sensing technology across the entire existing network is high – one supplier for North West England spent £30 million installing 100,000 acoustic loggers across its network [556] – and water companies report large numbers of their acoustic loggers not working due to failed batteries, incorrect attachment, communication failure, etc. [557]. Unlike previous studies using test-bed setups and new sensor technologies, this study uses real-world DMA flow data. This is significant as it seeks to verify that an existing and widespread method of sensing is able to provide sufficient data for highly accurate leakage detection in real DMAs. This could yield the environmental and economic benefits of reduced water loss (and the associated energy and resource savings) without requiring the cost of widespread deployment of new sensing technologies. Hence, the proposed framework can provide a greater level of resilience in existing and aged water infrastructure systems where the uptake of new sensing technologies is likely to be gradual.

4.1.2.2 Framework conceptualisation

In complex infrastructure systems, a vast number of individual components are often difficult to access (e.g. buried infrastructure). Hence, directly detecting failure via inspection can be prohibitively expensive and, to some extent, relies on noticeable/surface-level defects within the system. This can be costly to the resilience of both the system and the societies it serves and result in unsustainable and non-climate-friendly wastages, as well as monetary losses. Therefore, instead of directly observing failure in water infrastructure systems, operators rely on the data, often in the form of time-series data, from a sensor network to try and identify failure events. In such cases, data-driven- and machine learning-based models can offer a robust solution to the problem of failure detection [530] [531] [537].

An issue with time-series data can be the curse of high dimensionality [558] and the difficulty of developing damage detection cut-offs. This makes it hard to distinguish between essential information and noise within the data. To address this, many machine learning algorithms require some feature engineering, which is the application of domain knowledge to identify and select a subset of case-sensitive features from a dataset (e.g. mean, variance) to be used as input to these algorithms. AE neural network structures have effectively reduced dimensionality without requiring explicit feature engineering. Specifically, VAEs can produce smooth and regulated LVs that act as statistical surrogates for the input data by reducing the dimensions and capturing the key characteristics. Hence training and exploring the LV space of VAEs can provide high-dimensional insights within a low-dimensional space where the distance between the LVs indicates the similarity/dissimilarity within the characteristics of the input data. This offers an approach to identify any anomalies/failures (such as pipe bursts) in a lower-dimensional surrogate space rather than the original complex and high-dimensional space of the inputs (especially water flow in water infrastructure systems).

Within this setting, this study proposes a framework for leakage identification based on statistical surrogacy. Rather than directly classifying high-dimensional water flow time-series data into LKG or NLKG categories, the framework instead reduces the dimensions of the flow data using a domain-informed VAE to minimise the impact of redundant features and isolate the key components of different classes through surrogate LVs. Classification can then be performed on the surrogate LVs, which are trained to capture the distinction between the LKG and NLKG flow groupings through a domain-informed loss function. While other methods, including principal component analysis, can perform dimensionality reduction, a VAE is chosen for in this case as VAEs have proved to be effective on natural data [559] and in cases of extreme events [550], with leakage representing an extreme case of flow behaviour. Furthermore, due to the Bayesian nature of the VAE, the flexibility of altering the loss function provides an efficient solution to include the physics of the problem in the training process.

The proposed framework is illustrated in Figure 26. Sensors record the net flow of water for a given DMA at a discrete time interval (every 15 minutes in this case). The proposed framework uses a pre-specified length of the water flow record (the preceding 24 hours, i.e. 96 points, in this case) and classifies them into LKG or NLKG flow in real time using end-to-end pre-trained models of VAE and SVM. The framework starts by converting the preceding flow data into two surrogate mean LVs (i.e. μ_{LV_1} and μ_{LV_2}) using a pre-trained VAE encoder. The LVs are trained to be sufficient and efficient to contain information about the required characteristics of the water flow. The obtained μ_{LV_1} and μ_{LV_2} are then used as inputs for a pre-trained SVM, which compares these against the pre-obtained mapping of LVs to compute the probability of the flow data being classified as LKG ('burst') or NLKG ('usual') flow (i.e. $P(\text{LKG}) = P(\text{LKG}|\mu_{LV_1}\text{and } \mu_{LV_2})$ and $P(\text{NLKG}) = P(\text{NLKG}|\mu_{LV_1}\text{and } \mu_{LV_2})$). Then $P(\text{LKG})$ is compared against $P(\text{NLKG})$, and based on the greater value, the final classification decision is proposed (i.e. LKG/burst or NLKG/usual flow). Thus, this framework enables rapid monitoring of the water systems and flags possible leakages without human intervention. This information can then be used to inform the targeted repair strategies that minimise water loss in the network and curtail inconvenience to the public.

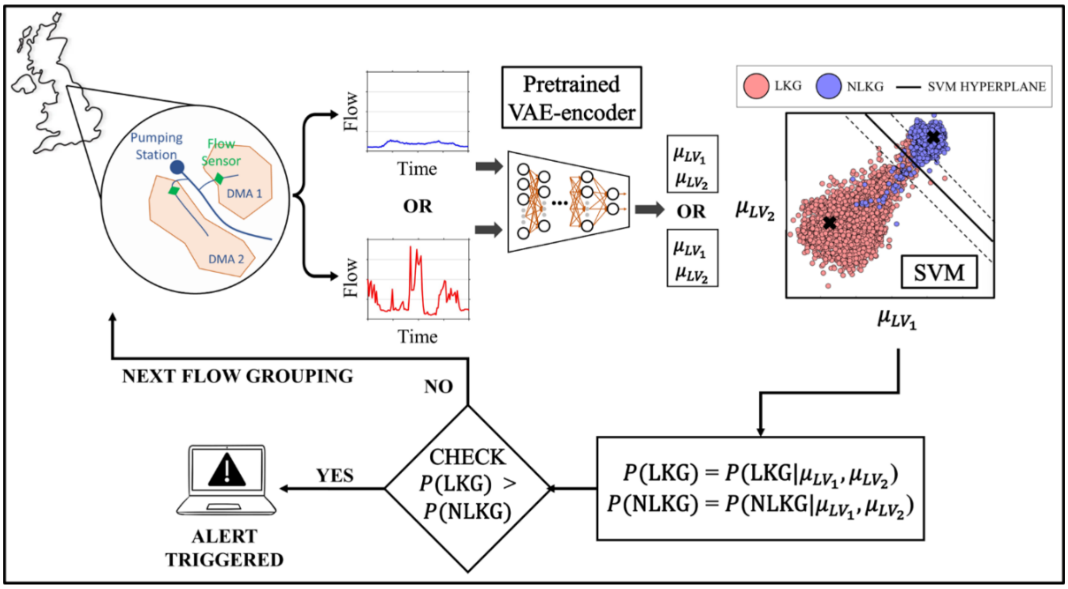


FIGURE 26: THE PROPOSED VAE AND SVM-BASED FRAMEWORK.

4.1.2.3 Training of the framework

The general procedure for training the proposed VAE-SVM is outlined here, with the details explained in the following sub-sections. As discussed in section 3.3, the ~10,000 LKG and NLKG flow groupings from over 2,000 DMAs are carefully processed and selected to train the proposed framework. The flow time series groupings are randomly split into train and test datasets, and the train data is used to train a VAE. The VAE aims to reduce the dimensionality of 96×1 flow time-series data into two sufficient and efficient surrogate LVs. The LVs map the flow time series onto a regularised two-dimensional variable space such that the LVs of LKG and NLKG groupings are maximally separated. The relative position of the LVs is based on the similarity/dissimilarity of the time-series groupings, which can be easily used to deduce the type of flow grouping. Hence, the VAE is trained to project the time series to a two-LV space. Then, an SVM classifier is used to create a decision boundary between the LVs of LKG and NLKG flow groupings to classify the LV. Once trained, the framework can map unlabelled flow time-series groupings onto the LV space and then probabilistically classify groupings as LKG or NLKG based on their position relative to the decision boundary. The framework’s two principal components, VAE and SVM, are described in the following sections.

A. Variational autoencoder (VAE)

VAEs are from the family of Bayesian neural networks, and their premise is based on AE neural networks [547]. AEs are a type of neural network used for the dimensionality reduction of vectorial data and are often used to find efficient data representations [548]. AEs consist of a neural network-based encoder trained with a neural network-based decoder. The encoder reduces the dimensionality of vectorial input data to produce LVs, a lower-dimensional embedding that seeks to capture the defining characteristics of the input data. The choice of LV dimensions is made based on the trade-off between the reconstruction power and explainability/visualisation of the LVs. Hence, this study uses a two-dimensional LV space to provide sufficient reconstruction power while ensuring the results are interpretable and explainable. The decoder then uses the LV space to reconstruct the input data effectively with minimal loss. While a standard AE maps the input data onto a deterministic LV space, in a VAE [547], the input data is instead mapped onto a probabilistic LV space with a pre-defined probability distribution. The LV space is compelled to possess smooth and continuous representations.

Consequently, points in closer proximity in the latent space led to similar reconstructions using the decoder. This is done using a neural network-based encoder (recognition model) trained with a neural network-based decoder (generative model) that can use the LV space to reconstruct the observations. This means that the encoder describes a probability distribution for each latent attribute from which values are randomly sampled to be fed into the decoder that is expected to accurately reconstruct the input. The LVs space is constructed using Bayes' rule given by Equation (5), where $\boldsymbol{X}$ represents the input vector (in this case 96×1 flow groupings).

$$p(LVs|\boldsymbol{X}) = \frac{p(\boldsymbol{X}|LVs)p(LVs)}{p(\boldsymbol{X})} \quad \textbf{(5)}$$

Traditionally, the VAEs are trained using a loss function consisting of two terms: i) reconstruction loss (denoted as $\mathrm{Recon\ loss}$) and ii) the Kullback–Leibler (KL) divergence loss (denoted as KL_{LV}) [560] [561]. $\mathrm{Recon\ loss}$ is the average of the mean squared error across the input and output (reconstructed input) vectors and measures how accurately the network reconstructs the original data (expressed in Equation (6) where n is the total number of input sequences, i is the sequence of interest, and $\boldsymbol{X}$ and $\widehat{\boldsymbol{X}}$ are the true and reconstructed vectors of time-series data respectively). On the other hand, KL_{LV} measures how closely the LVs match the target probability distribution (typically standard normal distribution as expressed in Equation (7) where n is the total number of input sequences, i is the sequence of interest, and $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are the mean and standard deviation vectors of the LVs, respectively). KL divergence is a directed distance measure that determines the deviation of one probability distribution compared to the other. Therefore, the higher the KL divergence, the higher the deviation between the two distributions. In other words, $\mathrm{Recon\ loss}$ makes sure that the LVs are sufficient and efficient representations of the input data $\boldsymbol{X}$ while KL_{LV} forces the LVs to possess a smooth and regularised target distribution space.

$$\mathrm{Recon\ loss} = \frac{1}{n}\sum_{i}^{n}\left(\boldsymbol{X}_i - \widehat{\boldsymbol{X}}_{\boldsymbol{i}}\right)^2 \tag{6}$$

$$KL_{LV} = \frac{1}{n}\sum_{i}^{n}\frac{1}{2}\left[-\sum_{i}\left(\ln\boldsymbol{\sigma}_i^2 + 1\right) + \sum_{i}\boldsymbol{\sigma}_{\boldsymbol{i}}^{\boldsymbol{2}} + \sum_{i}\boldsymbol{\mu}_i^2\right] \tag{7}$$

The conventional VAE loss terms penalise large differences between the inputs and reconstructed outputs ($\mathrm{Recon\ loss}$) and encourage regularisation of the LV space (KL_{LV}). However, in this study, the loss function is improved through an understanding of the physical problem that the proposed framework attempts to solve. The analyses discussed in section 3.3 establish that the leakages are associated with periods of anomalous flow (detected as outliers). Thus, to properly detect any leakages/bursts, it can be understood that the LKG and NLKG groupings should possess different characteristics. While the differences in characteristics can be challenging to identify in the original time-series domain, exaggerated differences in LV space (which is a sufficient and efficient representation of the original flow) can significantly improve the detection process. It is therefore important that the VAE is able to accurately capture the distinction between LKG and NLKG groupings in the LV space.

As a remedial measure, this study uses an additional 'domain-informed' loss term that drives the separation between the LVs of the two classes (i.e. LKG and NLKG). This is done mainly by computing the KL divergence (KL_{sep}) between the multivariate normal distributions of the LVs corresponding to the two classes (i.e. LKG and NLKG) as given in Equation (8) where $\boldsymbol{\mu_1}$ and $\boldsymbol{\mu_2}$ and Σ_1 and Σ_2 are mean vectors and covariance matrices corresponding to the two classes of LVs and n represents the number of groups [562] [563]. As can be understood from KL_{sep}, larger values of this term signify higher separation between the multivariate LV distributions of the two classes while lower values represent a higher degree of overlap. Hence, unlike KL_{LV} where the goal is minimising the difference between the LV space and target distribution (hence lower values are better), the objective of the KL_{sep} loss is having higher values representing better separation and distinction between the two classes of LVs (corresponding to LKG and NLKG). Therefore, KL_{sep} is added to the total loss of the VAE in an inverse manner as shown in Equation (9).

$$KL_{sep} = \frac{1}{2}\left[(\boldsymbol{\mu_2} - \boldsymbol{\mu_1})^T\, \Sigma_2^{-1} + \mathrm{tr}(\Sigma_2^{-1}\,\Sigma_1) - \ln\frac{\det|\Sigma_1|}{\det|\Sigma_2|} - n\right] \quad \textbf{(8)}$$

$$\text{Total Loss} = \text{Recon loss} + KL_{LV} + \frac{1}{KL_{sep}} \quad \textbf{(9)}$$

The overall loss function used to train the VAE penalises three items: i) improper reconstruction of the input sequence, ii) unregularised LV space, and iii) inseparable LVs across the two classes. This helps the VAE training process create distinct groupings in the LV space for the two classes, thereby improving confidence in LKG/NLKG classification. Alternative methods, including computing the distance between class centroids, calculating class overlap probability, and finding the margins of SVM classifiers, were also explored during the internal training trials of domain-informed VAE. Based on the performance and consistency of implementation, KL_{sep} loss is the final selection. KL_{sep} is also compatible with the KL_{LV} loss that is inherent to the VAEs. Hence, the purpose of the VAE in this study is to produce an LV mapping that shows the separation between the LVs of different types of flow time-series groupings (LKG and NLKG), by capturing the different characteristics of these data groupings via dimensionality reduction. In addition, LVs must be efficient and sufficient to reconstruct input data.

For training the VAE in this study, the LKG and NLKG groupings are standardised and split into train and test sets such that 80% of both groupings are used in training (with 10% cross-validation), and 20% of both groupings are used for testing the VAE. Various configurations of VAEs were trained through grid search and hyperparameter tuning approaches [47] [48], to select the best-performing VAE architecture. Performance here is measured by IA of reconstructed data, classification accuracy of the SVM on the LV distribution, and visual clarity of the LV distribution. The hyperparameter variations consisted of different: numbers of layers, number of neurons, activation functions, optimisation algorithms, batch sizes, epochs, and dropout rates. Further detail on some elements of the hyperparameter tuning is provided in Appendix A. Trials were also conducted exploring the benefits of a three-dimensional LV space rather than a two-dimensional space. See Appendix B for a selection of examples. Ultimately, it was decided that a two-dimensional space offered comparable or improved accuracy while maintaining better visual clarity. The final optimised VAE is presented in Figure 27. The proposed VAE consists of nine layers in each of the encoder and decoder (including the input and output layers) with a total of 1,244 neurons and a bottleneck to produce two independent, normally distributed LVs. The activation function for each layer is hyperbolic tangent (tanh) except for the output layer of the decoder, which is linear [566]. The train set is shuffled into mini batches of 128 and used to train the VAE in 500 epochs using the adaptive moment estimation (Adam) [523] optimiser and early stopping [567] regularisation.

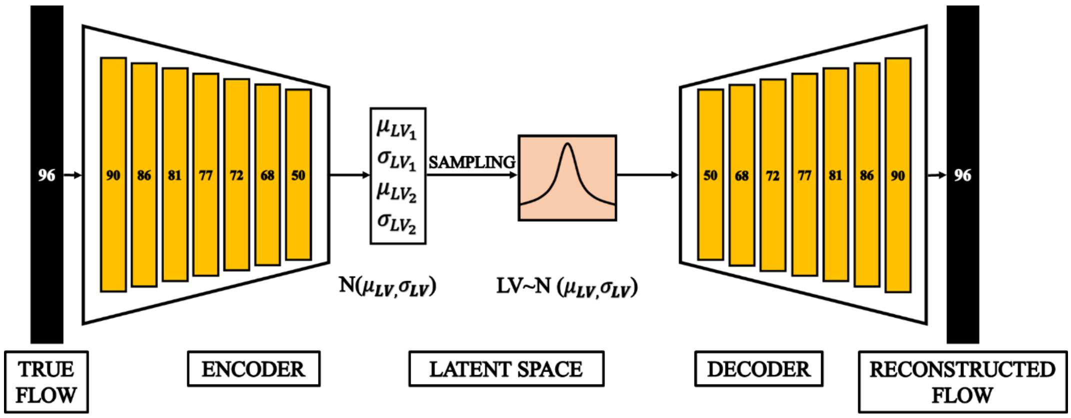


FIGURE 27: THE SELECTED ARCHITECTURE OF VAE (NUMBER OF NEURONS OF EACH LAYER IS DISPLAYED IN THE CELLS).

B. Support vector machine (SVM)

SVM is a supervised machine learning algorithm that can be applied to both regression and classification problems [568]. Since this study aims to train a model capable of accurately detecting the separation between the two classes of LVs, a binary SVM is deemed sufficient. The binary SVM is a linear classifier that, given training data and corresponding class labels, finds an optimal boundary in the feature space to maximise the separation between two classes. This boundary is called the optimal hyperplane [569]. SVM classifiers identify the points closest to the hyperplane as support vectors. The support vectors influence the position and orientation of the optimal hyperplane. By maximising the thickness of the hyperplane (thereby distance between the support vectors), SVM allows the feature space to be divided into regions that represent the known classes. A hyperplane can be described by Equation (10). The optimal hyperplane given in Equation (10) is obtained through the optimisation of Equation (11). Real data often contains outliers, and thus is rarely linearly separable, so a soft margin SVM adds slack variables and regularisation to deal with noisy data [570]. Once the SVM has been trained and the hyperplane is obtained, new unlabelled data can be probabilistically classified by mapping into the feature space and noting position relative to the hyperplane.

$$\boldsymbol{w} \cdot \boldsymbol{V} + b = 0 \quad (10)$$

where $\boldsymbol{w}$ is the weight vector, b is the bias, and $\boldsymbol{V}$ is the input data.

$$\min_{\boldsymbol{w},b} \frac{1}{2} \|\boldsymbol{w}\|^2 + C \sum_{i}^{n} \zeta_i \quad (11)$$

Subject to $k_i(\boldsymbol{w} \cdot \boldsymbol{V}_i + b) \geq 1 - \zeta_i$, with $\zeta_i \geq 0$, for all $1 \leq i \leq n$. Where n is the total number of input samples, $\|.\|$ is the matrix norm, and $C > 0$ is the regularisation constant. ζ is the slack variable, with $\zeta_i = 0$ for regular points and $\zeta_i > 0$ for outlier points. k is a variable such that negative classes have $k = -1$ and positive classes have $k = 1$.

In this study, an SVM is used after the trained VAE encoder maps the flow grouping data into the LV space in order to utilise the trained hyperplane to probabilistically separate the LVs of the LKG and NLKG classes. First, the training of the SVM hyperplane is conducted using the LVs of the training dataset along with their associated LKG/NLKG class labels. Of over the 8,000 samples in the training dataset, 383 points are selected as support vectors by the SVM, which are used to maximise the margin of the classifier and thereby classify the LV data. Once the proposed framework is provided with unlabelled 96×1 water flow data, it maps the flow onto the two-dimensional LV space using the pre-trained VAE encoder. Finally, the pre-trained SVM uses the mapped LVs to determine the probability of the input flow data being classified as LKG and NLKG.

4.1.3 Restoration Process

4.1.3.1 Background

The task of repair scheduling is addressed in numerous infrastructure sectors and civil engineering contexts, including construction, buildings, rail and road networks [571]. Research on scheduling in water systems has been less extensive, but this field is growing and several interesting approaches have emerged [572].

A significant focus of research on repair scheduling in water distribution systems has been the restoration of pipe networks following natural disasters such as earthquakes [101] [573] [574] [575]. As data on such events is understandably limited and leakage and repair efforts are not always well-documented, most studies demonstrate their methods on simulated data produced via techniques such as hydraulic analysis [79] [80] [81].

Approaches to repair scheduling can be described as either single-objective or multi-objective methods. In water systems, the objectives chosen might include minimising indicators such as water loss, repair cost, repair time, and disruption of service, and maximising indicators such as system resilience and overall asset health [572] [100] [574]. Analysis of factors influencing repair sequencing shows, in a disaster situation, that the significance of factors can vary in different scenarios [575]. However, in such time-sensitive situations, there is a need to balance the longer run time of complex multi-objective models with the need for rapid outputs [576]. In disaster response scenarios, approaches vary from a dynamic cost-benefit method [81] to prioritisation of restoring water supplies to emergency facilities such as hospitals and fire stations [95].

Research on day-to-day repair scheduling in water distribution systems has been less extensive [572]. The limited studies in this field take care to emphasise the importance of an optimised repair strategy for improved life cycle management, while considering budget constraints at a network level [577] [578] [579] [580] [581]. A variety of approaches are taken, including a prioritisation algorithm based on rank aggregation [579], a risk-based economic life cycle cost analysis approach [578], and a genetic algorithm for repair scheduling as a multi-objective problem [577] [582] [581]. It is additionally recognised that repair strategies that include multiple interconnected infrastructure systems could further optimise resources [583] [584]. In water systems, an example of this would be the replacement or upgrading of water distribution pipes and sewage pipes in a coordinated repair, so that the surface pavement is only replaced on a single occasion [572]. In the context of pipe leakage, however, it is important to consider the trade-offs of water loss, cost, and disruption, and large leaks may need to be prioritised even if coordinated repair with other systems is not possible.

Genetic algorithm-based approaches are perhaps the most widely used method for multi-objective repair optimisation in water systems [584] [100] [577] [582] [581]. Genetic algorithms are inspired by Darwin's theory of evolution and are used to solve complicated problems with a large number of variables and possible outcomes or solutions. Combinations of different solutions are passed through the algorithm to find the best solutions, with worse solutions replaced by the 'offspring' of better solutions [585]. Genetic algorithms demonstrate robust search abilities, making them well-suited for the complexity of large-scale optimisation problems such as pipe repair scheduling [577].

A new and exciting approach to repair optimisation is offered in reinforcement learning [586] [587] and deep reinforcement learning [588] [589]. Reinforcement learning can adapt and learn from feedback to make more efficient decisions over time. By leveraging rewards and penalties, reinforcement learning methods can optimise repair schedules based on real-time conditions, reducing downtime and maximising resource utilisation. Furthermore, reinforcement learning can handle complex and dynamic repair scenarios, considering multiple factors and dependencies to generate optimal schedules that improve overall efficiency [590]. Reinforcement learning can be combined with deep learning methods to overcome some of the limitations of traditional reinforcement learning in high-dimensional and complex stochastic domains [588]. In water distribution systems, one study combines a graph convolutional network with deep reinforcement learning to determine the optimal repair sequence for a testbed network in a post-earthquake scenario, with this method able to achieve a resilient system recovery in very reasonable computational time [573].

The literature explored here presents several promising approaches for repair optimisation in the field of water distribution systems, and there exists significant potential for further exploration of sophisticated repair optimisation methods based on new and evolving methods such as deep reinforcement learning. The restoration process can therefore be developed to include cutting-edge methods to the same extent as the anticipatory and detection processes presented in this study and should not be an afterthought.

However, this study is limited by the lack of available data at the individual component level. As additional information (pipe properties and network layout, repair equipment and crew availability etc.) is not available to this study, and the goal of this case study is to demonstrate comprehensive self-healing on historical (and not simulated) data, a simpler method of repair prioritisation is chosen in this instance. The benefit of incorporating a simpler method for this process is that it demonstrates the flexibility of the self-healing framework. Many water companies may not have the resources or training necessary to implement the latest in machine learning methods, but the self-healing framework can be applied to any level of modelling maturity. This demonstrates that companies do not need to wait until they are able to apply advanced modelling techniques to benefit from a self-healing approach. Therefore, a simple single-criterion approach is used in this study to prioritise the leakage forecasted and identified by the anticipatory and detection processes. This approach prioritises tackling the most severe leakages in the system, giving equal weight to forecasted and detected leakages.

4.1.3.2 Framework conceptualisation

As this study does not have access to detailed data at the pipe component level, a framework is developed that instead can generate a prioritised list of leakage at the DMA level for a given moment in time. It is expected that the list would be updated in real-time as new leakage is both forecast and identified, as forecasted leakage become detected leakages, and as repairs are carried out. From this list, a prioritised list of DMAs is obtained that gives repair exploration crews an order in which to visit DMAs that will target the most those with the most severe leakage (either forecasted or identified). The framework is presented in Figure 28.

This framework assumes that the prioritisation is done under typical operating procedures, rather than for a disaster response scenario. Hence, the system is assumed to be operational at all times and there is no additional consideration given to the supply of critical infrastructure such as hospitals.

A single-criterion method based on Z values is selected due to the limited data on DMA and pipe characteristics. This method prioritises leakage that is most severe relative to the usual flow data in the DMA. This relatively straightforward single-criterion method is also chosen as it demonstrates the flexibility of the overall self-healing framework. Each process must be designed with the data flows of the other processes (and the infrastructure system) in mind, but the methods used for a given process can be at any level of sophistication. Methods for each process can therefore be substituted out for more advanced methods should such methods be better suited to the available data, but the transition to more sophisticated methods can be done gradually and in a way that does not require an upfront overhaul of operating practices. As operators are trained in relevant skills, it may become more appropriate to include more complex methods for a given process.

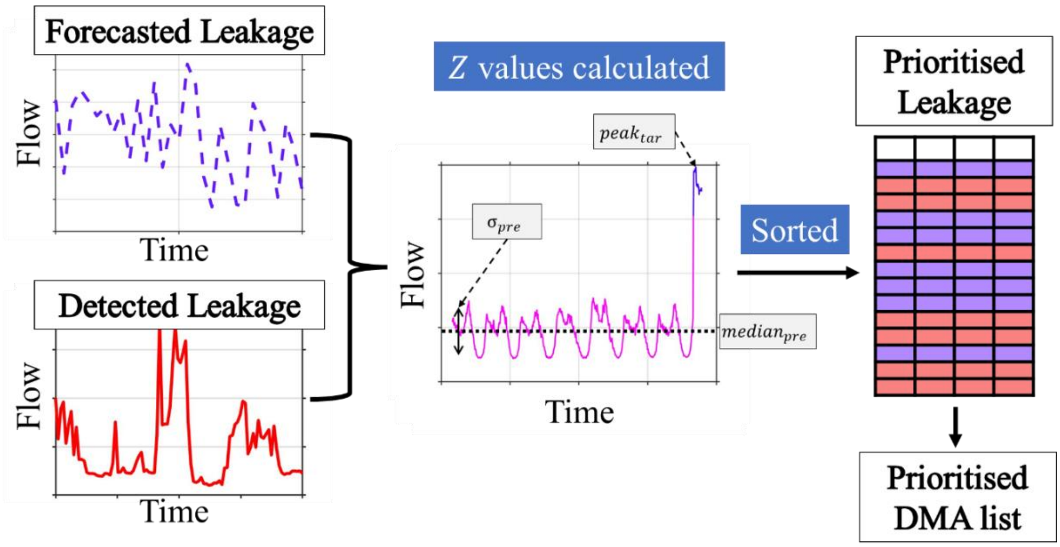


FIGURE 28: THE PROPOSED LEAKAGE RESPONSE PRIORITISATION FRAMEWORK.

4.1.3.3 Applying the framework

A straightforward method combining outputs of both the anticipatory and detection processes is used to assess the priority of potential leakage.

A random date within the year of provided flow data is selected to demonstrate how previous and incoming data might be combined to create a prioritised list of inspection or repair jobs. The detected leakage corresponding to the preceding week is then extracted from the outputs of the detection process. It is assumed both that no outstanding leakage jobs exist prior to this and that none of the detected leakage from this preceding week have been addressed. In this case, the time of 00:00am of the 12th September 2016 is selected as the point from which detected and forecasted leakages are combined. All potential leakages detected in the preceding week (5th to 11th September) are extracted, with any entries that share the same DMA ID as another entry for the same period flagged as repetitions. This is as numerous leakage issues within the same DMA may represent either the same leakage event or perhaps be indicative of wider problems in the set-up of the DMA (for example, leakages occurring in an adjoining pipe once a pipe has been replaced due to underlying issues with flow or pressure). Flagging DMAs that show repeat instances of potential leakage thus brings to the attention of investigators or repair crews the possibility of these underlying issues in the DMA, and these teams can further investigate if necessary. Furthermore, in the absence of any additional data on DMA locations relative to each other, flagging repeated DMA IDs allows repair crews to optimise their time by attending multiple leakages (if indeed repeated leakage alerts are found to indicate separate events) within the DMA as part of the same trip. The forecasted leakages from the 12th of September through to the 18th of September are then extracted and combined with the detected leakages. If a DMA appears in the forecasted dataset after it is already present in the detected dataset, or appears multiple times in the forecasted dataset, it is again flagged as a repeated DMA ID.

In this simple analysis, a single parameter is selected as a metric for leakage priority. As discussed in the above background section, more complex, multi-criteria methods can be applied, and the possibilities increase with additional data. In this study, no data is available for the repair capabilities of the water company managing the DMAs. Hence, a simple single-criterion method is selected to demonstrate how this restoration process can be integrated into the wider self-healing process even if data is relatively limited. As covered more in section 5.3.2, this restoration process acts as a separate block which, provided it is set up to accept input data of the same type as the output data of other processes, can be substituted for methods of various complexity.

The parameter selected for leakage priority in this study is the Z values for the detected and forecasted leakages. Z values require a period of flow preceding the leakage in order to contrast flow behaviour during the leakage with ‘regular’ flow behaviour. The process for calculating the Z value of a given leakage grouping is given in Equation (12). In this equation, $peak_{tar}$ represents the largest flow of the LKG section (the subscript tar here represents the targeted flow section - this is the recorded flow for the detected leakages and the mean forecasted flow for the forecasted leakages) and med_{pre} and σ_{pre} are the median value and standard deviation of the preceding flow data respectively. The Z value thus compares the magnitude of the peak of the targeted flow sequence to the average magnitude and variability of the preceding flow data, as illustrated in Figure 29, thereby indicating the magnitude of the outlier. Z values can therefore be said to give an insight into the severity of the leakage.

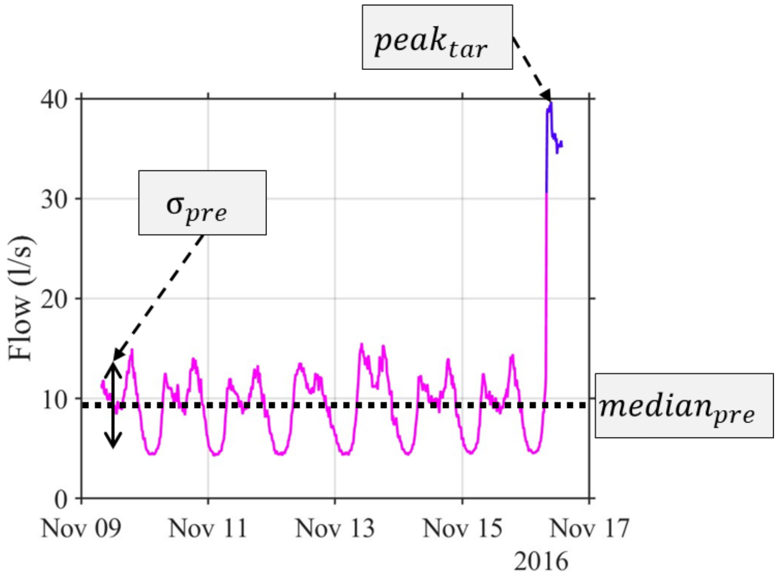


FIGURE 29: THE STATISTICS REQUIRED TO CALCULATE THE Z VALUE OF A LKG GROUPING.

$$Z = \frac{|\ (peak_{tar} - \ median_{pre})\ |}{\sigma_{pre}} \tag{12}$$

The reason that Z values are used rather than just peak flow values is that the variation in the diameter of pipes and the size of DMAs means that typical flow magnitude varies significantly between DMAs. Using only peak values does not account for the typical flow magnitude within a given DMA, so a high peak magnitude in a LKG grouping could represent either a large leak in a DMA which usually has low to moderate flow or a small leak in a DMA which usually has high flow rates.

The Z values for each of the LKG events in the dataset of detected leakages from 5th to 11th September are calculated. As these events have occurred in the 'past', relative to 12th September, the prioritised repair list is created by sorting them by their Z values.

The forecasted LKG groupings for 12th to 18th September represent incoming 'live' events. As these would be added to the repair priority list in real-time, based on a live forecast, this dataset is first sorted by the date and time at which the forecast indicates a leakage event. Z values are then calculated for these forecasted LKG groupings. These can then be added to the existing list of leakages to represent how this would be updated to include incoming leakage forecasts. The Z value of an incoming forecasted LKG grouping is used to determine its position on the prioritised repair list.

4.2 RESULTS

This section presents the results of the frameworks when trained and tested on the dataset of over 2,000 DMAs (this dataset is described in section 4.1). The data used in training and testing each framework is subject to the pre-processing described in section 3.3.

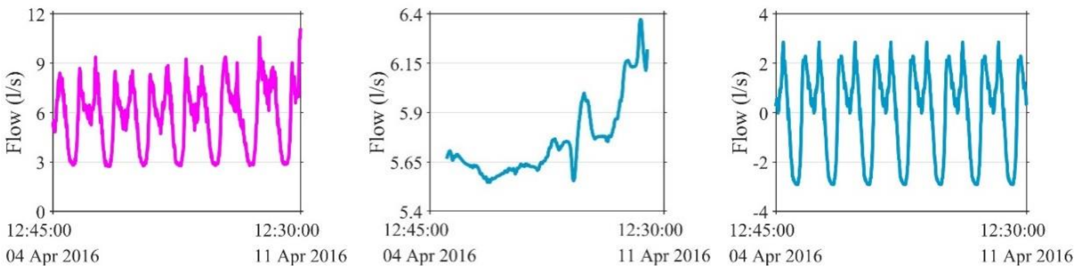
4.2.1 ANTICIPATORY PROCESS

4.2.1.1 Introduction

This section presents the results of the trained framework for the anticipatory process on the flow time-series data. The following sections discuss the results of the mean flow forecasting and residual forecasting components separately, and then the results of the combined forecasting process are explored.

4.2.1.2 Mean flow forecasting

Figure 30 illustrates the outcome of time-series decomposition on exemplar input data. The trend component shows the overall pattern of change in flow across a week, while the seasonal component captures the daily flow pattern. This typical pattern, with twice-daily peaks and a significant drop overnight, reflects typical water consumption over 24 hours and is seen in most input data. The trend component is more variable across LKG/NLKG input groupings, as this is affected by factors such as which (and when) days of the week appear in the input data and if and how leakage is reflected in the input data. In order to ensure all relevant patterns are considered, these two components are separately input into the RNN.



(A) (B) (C)

FIGURE 30: DMA 586 OUTLIER 1 (A) INPUT DATA, (B) TREND COMPONENT, (C) SEASONAL COMPONENT.

The trained RNN uses the flow data's trend and seasonal components as inputs and predicts the flow for the future 335-time-steps (i.e. LKG/NLKG data for 335 15-minute intervals). IA values are calculated for each grouping to assess how well these predictions align with the observed LKG/NLKG data. IA, described earlier in Equation (4), gives a single bounded metric for pattern characterisation and comparison yet also incorporates information on the magnitude of deviations. IA is therefore a valuable tool for the comparison of model performance and has been widely applied to the assessment of time-series models [46]. The left part of Figure 31 presents the distribution of IA values for all the groupings. Overall, this IA profile indicates good performance by the RNN, with predicted values and observed flow in good agreement. The vast majority of groupings have an IA value over 0.5, with a first peak between 0.5 and 0.6 and a second, more prominent peak between 0.8 and 0.9. The reason for these peaks may be differences in the 'type' of grouping, so factors that vary between groupings are further investigated.

Due to different magnitudes of outliers, LKG groupings vary significantly in length and volatility (volatility describing the magnitude of LKG flow compared to the magnitude and variance of preceding input flow). Hence, it is necessary to ensure that the RNN predictions are not biased towards LKG groupings with little volatility compared to groupings with significant volatility. Hence in this study, a standardised measure of volatility (i.e. the difference in the magnitude of the LKG flow compared to the magnitude and variance of preceding flow) is computed for each LKG grouping. This measure is Z value, which is introduced earlier in Equation (12). The Z value thus compares the size of the output peak to the size and variability of the preceding input data. As can be observed from Figure 20 (in sections 3.3), the peak of NLKG flow is not as high as the peak of LKG flow when compared to the median of the preceding input flow. Also, peak flows can vary significantly based on the burst level within the LKG groupings. Therefore, computing the Z values and comparing them against the corresponding IA values allows the detection of any unintended bias in the model.

Furthermore, since the LKG/NLKG parts of the groupings vary in length and are zero-padded (as described in section 3.3), it is essential to check any potential bias in the LSTM-RNN predictions concerning the non-zero padded length of the output data. The right side of Figure 31 shows the IA values for all the ~10,000 samples compared to the output data's Z values and non-zero padded length. The colour of each dot represents the Z value of each grouping. It is observed that 25% of the selected LKG groupings have a Z value greater than 5, with a low probability (less than 0.00001) of randomly having Z > 5, and the median Z value of LKG groupings is 2.1, with a probability of $Z > 2.1$ being less than 0.035. This confirms that the pre-processing method has captured genuine outliers in the dataset. Furthermore, the additional criteria for LKG group selection ensures the capture of flow patterns typical of leakage, characterised by a significant spike in flow data that surpasses the fluctuations in preceding data.

As the most extended LKG group is 335 data points in length, many groupings possess this length without any zero padding (especially NLKG data). While higher values of IA are observed across the different LKG group lengths, the concentration of higher Z values in the top left of the plot suggests that the proposed model performs particularly well on leakages with large flow magnitudes and shorter LKG lengths. This may indicate that the preceding flow data for such LKG groups follow a more identifiable pattern captured by the LSTM-RNN. While this is an interesting hypothesis, it is beyond the scope of this research to statistically investigate this. Conversely, the lowest IA scores are seen in LKG groups with common Z values, suggesting that the LSTM-RNN struggles to forecast accurately if the peak values are small and the variability in the preceding flow is high.

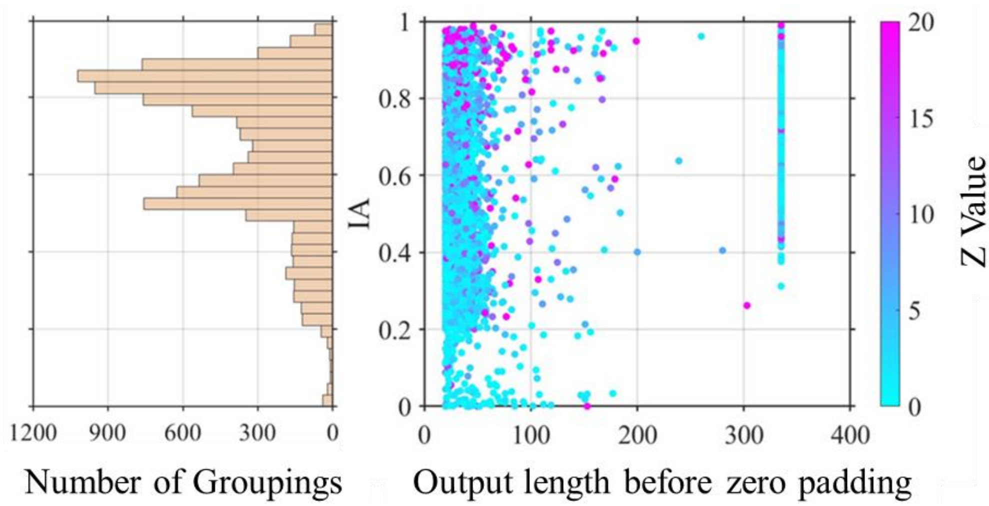


FIGURE 31: IA VALUES, Z VALUES, AND OUTPUT LENGTHS (WITHOUT ZERO PADDING) OF ALL GROUPINGS.

To check the patterns of the LSTM-RNN predictions against the recorded output flow, Figure 32 shows four quantile cases from the test data (20% of the dataset). Each of these cases represent a period of anomalous flow data flagged as LKG, rather than a period of regular, non-anomalous flow. While there are some fluctuations, the LSTM-RNN forecasts largely follow the overall pattern of the recorded flow data in both magnitude and direction of change (increase/decrease). In some areas, the flow forecast fluctuates more than the recorded data. In most cases, as seen in the examples shown for the 50th, 75th, and 99th IA percentiles in Figure 32, this fluctuation tends to be distributed relatively evenly above and below the flow profile of the recorded outlier, suggesting that the overall pattern of flow is well captured. All four examples in Figure 32 see a higher forecast value for the first forecast flow datapoint than the recorded flow value. In terms of leakage management, that the LSTM-RNN is more inclined to an initial overestimate than an underestimate means that leakage is less likely to be missed by the model. However, particularly at the higher IA percentiles, the overestimation and underestimation in the prediction across the entire forecast window seem well balanced. Therefore, the model could be expanded to offer an accurate prediction of the quantity of water loss via leakage. It is observed that even at 25th percentile, the IA value exceeds 0.5, with IA rising to over 0.7 at the 50th percentile. Forecast accuracy, and thus IA values, can be expected to improve with the addition of residual forecasting using the KF.

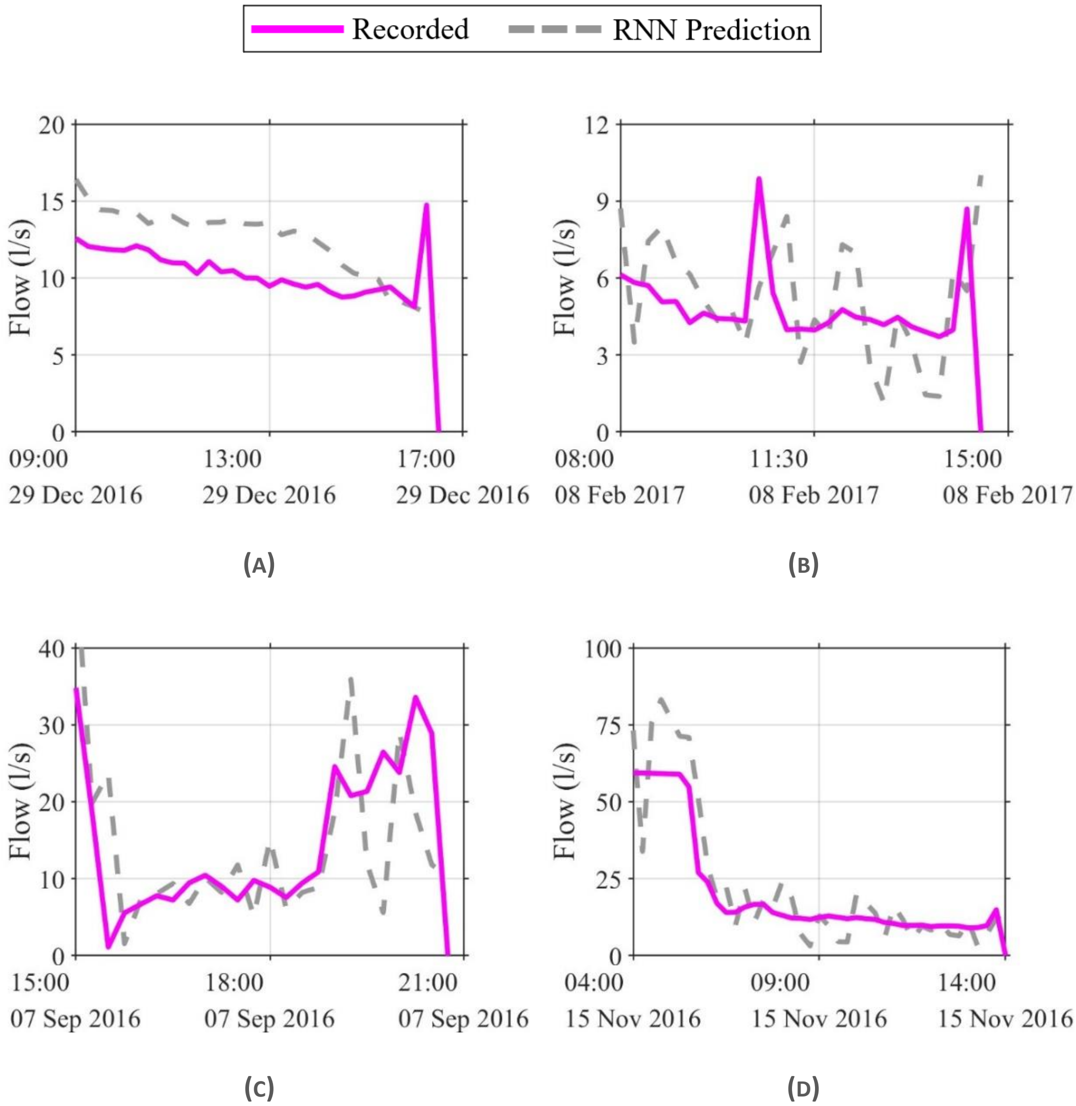


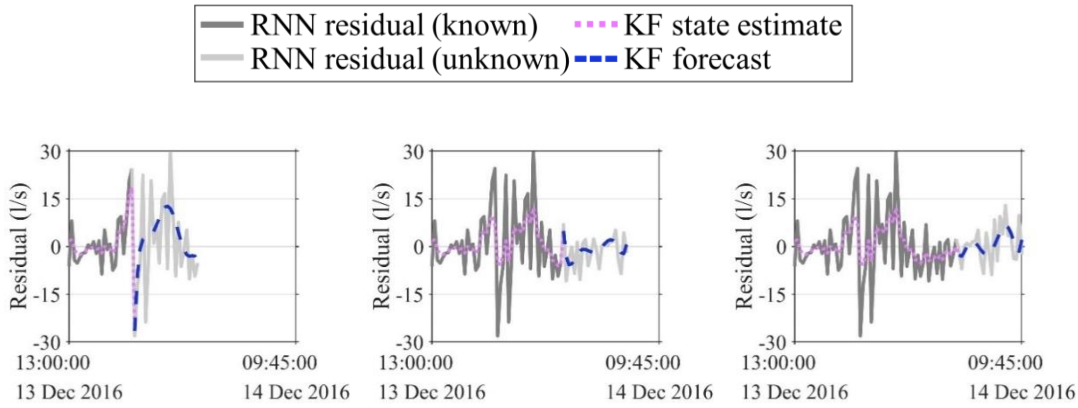
Figure 32: Examples of true vs LSTM-RNN predicted flow for: (a) 25^{th} percentile: DMA 1672 outlier 3 (IA =0. 5362), (b) 50^{th} percentile: DMA 1999 outlier 2 (IA =0.7098), (c) 75^{th} percentile : DMA 189 outlier 4 (IA =0.8307), (d) 99^{th} percentile : DMA 1085 outlier 2 (IA =0.9554).

4.2.1.3 Residual forecasting

As the LSTM-RNN model is trained to estimate the mean flow using the known trend and stationary components of the preceding flow, the weights of the LSTM-RNN network are pretrained. They are expected to perform the flow forecasting with known causality. However, to improve the proposed framework's real-time performance, the residuals obtained in real-time are further used to develop the state-space model using KF to appropriately forecast the future residuals. Using the pre-trained LSTM-RNN, the flow forecast is obtained from current time t to n time-steps ahead to $t + n$ time, and then as the true values of flow are observed in real-time for time-steps t to $t + k$, where $k < n$, KF is used to model the residuals by finding the difference between the LSTM-RNN forecast and the recorded flow. Due to the recursive nature of KF estimates, this process is expected to provide the framework with real-time deviations of the data and improve the accuracy of the hybrid forecasting system. The results of KF-based forecasting of the LSTM-RNN residuals are presented for an exemplar DMA in Figure 33. This example chooses a prediction window of six hours (24 data points).

As the observed values are considered to be the sum of the underlying state plus noise, KF is performed on known residuals (time-steps ≤ t) before forecasting so that the prediction can be based on the estimated state rather than the observed values. KF is then used to obtain a forecast for *n* time-steps ahead. As more data points for the flow are recorded, the residuals are computed, and the updated model is used to forecast the residuals for a future time window. Figure 33 shows the estimated states for t = (a) 24, (b) 48, and (c) 60 and KF forecast for n = 24 during a period of LKG flow, demonstrating how the KF is used to provide a forecast of residuals with a real-time rolling time window. It can be observed that forecasting power is improved as more residuals are provided to the model. The KF demonstrates strong performance in both state estimation of known residual data and forecasting the unknown residual data. The state estimation step smooths the observed data, with the estimated states showing less volatility than the observed residual values.

Similarly, while the forecast can predict changes in the overall trend of the residual data, many peaks in the observed residual data appear less extreme in the forecasted data. Although huge spikes in residual data may be underestimated in the forecast, the KF effectively captures the overall pattern of residuals. Therefore, adding residual forecasting to mean flow forecasting will allow real-time updates to forecasting and improve the accuracy of the final combined prediction.



(A) (B) (C)

FIGURE 33: RESIDUAL PLOTS FOR 24 STEPS AHEAD, DMA 1316 OUTLIER 1 WITH: (A) 24, (B) 48, AND (C) 60 INPUTS.

4.2.1.4 Final flow forecasting

Finally, the results of the LSTM-RNN and KF predictions are combined to obtain a final flow forecast. This is presented for an example case of LKG from the test set in Figure 34. Note that the x-axis is split to provide greater detail for the forecasted section of flow. In this example, 60 residuals are provided for a forecast window of 24 residuals. It can be observed that the combined forecast appears to match the recorded outlier well. The forecast anticipates the fluctuations in flow for the outlier period, during which the daily water consumption pattern is much less precise than for the input data. The forecast also matches the peak of the outlier well in both magnitude and time, though both peaks and dips can be overestimated in the prediction.

Captured in this example is both an elevated daytime and night-time flow, relative to the input data. The prediction also captures the significant drop in flow from day to night, despite the leakage. This drop corresponds to the overnight period often used to calculate

MNF in other leakage identification studies. The forecast captures both the reduction in water usage from day to night and the elevated night-time flow level indicative of leakage in studies using MNF. In shorter outlier groupings where the night-time period is not represented within the outlier grouping, extending the forecast beyond the outlier period may be beneficial to verify whether the predicted minimum remains elevated compared to overnight periods in the input data, which would be expected during leakage. As this prediction shows strong agreement with the recorded data throughout the outlier period, not just the overnight section, and the increased MNF is accurately anticipated by the forecast, it is shown that this method, unlike many traditional leakage identification methods, does not necessitate a full overnight period of flow data to identify leakage. Instead, anomalous flow behaviour can be accurately determined and anticipated during daytime hours. This allows for more rapid flagging of leakage and thus can facilitate more timely and less disruptive repairs. For the LKG group shown in Figure 34, the LSTM-RNN mean flow forecast has an IA of 0.8466. When combined with the residual forecast, however, the IA for this group rises to 0.9240. This improvement demonstrates the value of this hybrid modelling method.

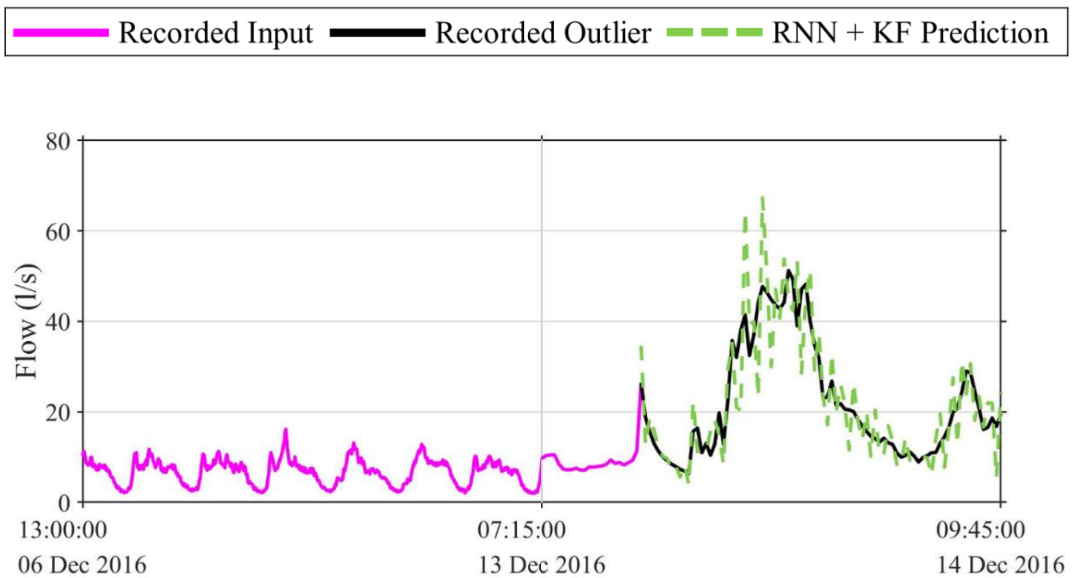


FIGURE 34: FORECAST FOR DMA 1316 OUTLIER 1 (IA = 0.9240).

4.2.2 DETECTION PROCESS

4.2.2.1 Introduction

This section presents the results of the trained framework on the train and test datasets of the flow time-series. The following sections discuss the LVs obtained from the VAE and the accuracy of the SVM classifier.

4.2.2.2 VAE

The dataset utilised in this study contains leakages detected through outliers, which can differ significantly in magnitude. Since such different outliers are used to train the VAE (hence the LVs), it is important to assess the nature of the LVs with respect to the magnitude of outliers. Again, Z values are computed for each of the LKG and NLKG groupings using Equation (12). The Z values compare the magnitude of the peak of the recorded flow sequence to the average magnitude and variability of the preceding flow data. The comparison of the Z values against the corresponding LVs for each grouping provides insights into the LVs. The means of the LVs (μ_{LV_1} and μ_{LV_2}) are presented in Figure 35, with each point colour-coded as either LKG or NLKG along a colour gradient set by the corresponding Z values.

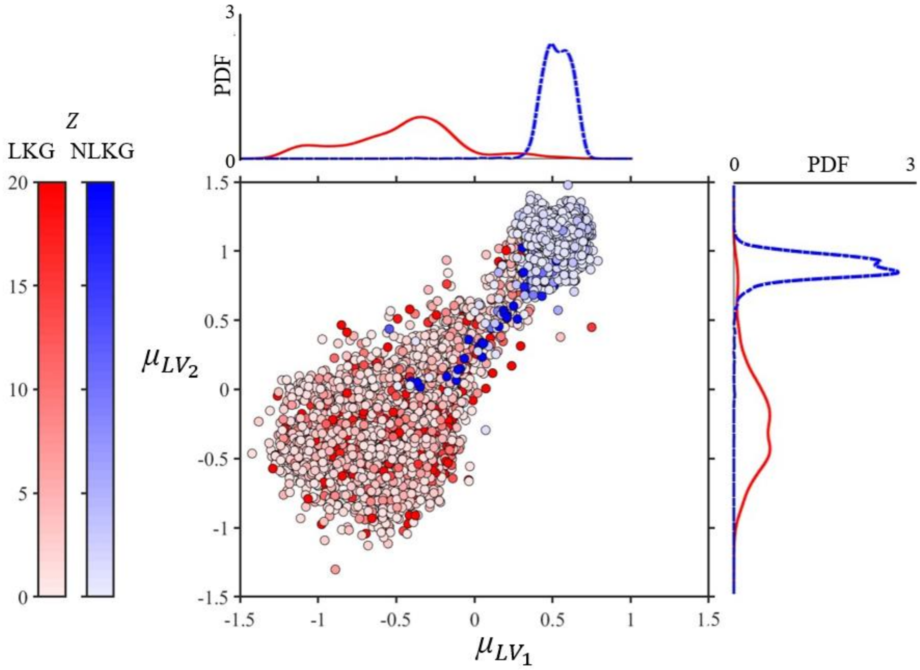


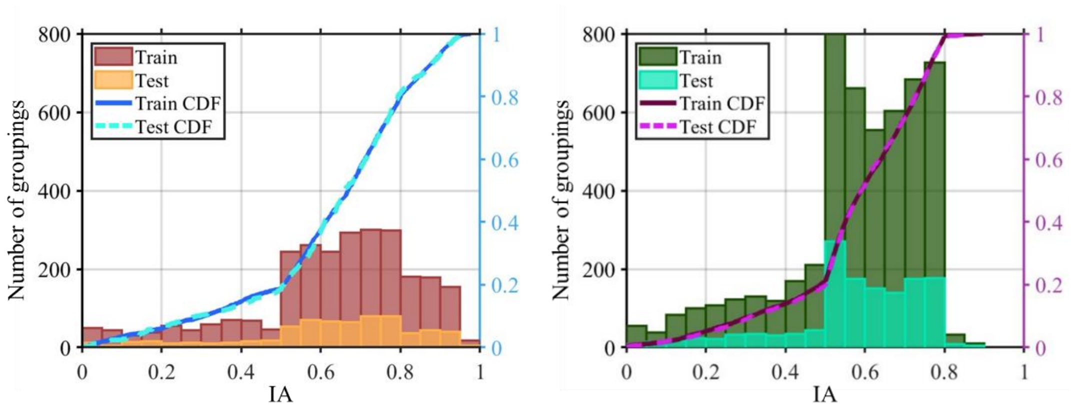
FIGURE 35: MEAN LVS (μ_{LV_1} AND μ_{LV_2}) OF THE TRAINED VAE.

Figure 35 shows clear groupings of μ_{LV_1} and μ_{LV_2} for LKG and NLKG data. There are minimal overlap in the probability density functions (PDF) distributions of the two groupings for both mean LVs, with a distinct and dense cluster of NLKG LVs and a largely separate, though more spread, cluster of LKG LVs. The difference in the spread of the clusters can be accredited to the fact that the LKG groupings are generally uniform (Figure 22a, in section 3.4) and obviously fluctuate less dramatically than the outliers NLKG groupings (Figure 22b, also section 3.4). Hence the corresponding mean LVs are narrowly spread for the NLKG groupings. A significant majority of NLKG data leads to μ_{LV_1} between 0 and 1, and μ_{LV_2} between 0.5 and 1.5. The PDF kernels for the mean LVs of NLKG show sharp spikes in these ranges, indicating a dense concentration. As mentioned earlier, this narrow variance in the LV space suggests minimal variation in the characteristics of the initial time-series data of the NLKG groupings. The dimensionality reduction leads to similar features in the input data. The Z values are represented in the red and blue colour gradients for the LKG groupings and NLKG groupings respectively. The mean LVs for the LKG groupings show no great difference between those with high Z values, indicating higher volatility in the outliers, and those with low Z values. The NLKG groupings lead to low Z values, as expected for non-outlier data, and are shown in the dense groups of pale blue points. A few exceptions are observed for the NLKG groupings with particularly high Z values, indicating greater volatility in the original time series than the majority of NLKG groupings. Analysis of these NLKG groupings with high Z values shows that the flow time-series data for these groupings is typically very low in magnitude, which can be due to differences in DMA size and pipe diameter, as well as supply issues. Such low flow values are thus more likely to produce high Z values as even minor fluctuations are more significant in lower flow values. Detecting leakage in lower volume pipes can therefore present more of a challenge than detecting leakage in higher volume pipes, although the water loss is expected to be much less for leaks in lower volume pipes.

The μ_{LV_1} and μ_{LV_2} corresponding to LKG data have a greater spread, with PDF curves showing lower peaks and higher variances. This can be due to the higher variability in the characteristics of the input time-series of the LKG groupings. The spread does not differ significantly across corresponding Z values. This suggests that the volatility of LKG groupings (relative to preceding non-leakage flow) is not the only characteristic influencing the dimensionality reduction process. Hence, the training of VAEs leads to surrogate LVs that may capture other behaviours of the LKG time-series (e.g. the sustained value of peaks etc.). However, such analysis is out of the scope of this study.

The reconstruction power of the VAE is assessed using IA [519], [520]. It is worth noting that the primary goal of the proposed framework is to train surrogate LVs that allow for accurate classification of LKG and NLKG flow groupings through SVM, and therefore an accurate reconstruction of the input groupings is not the main goal of the study and only serves to improve confidence in the surrogate LVs. Hence, IA of the ~10,000 flow groupings provide an additional indicator of the strength of model performance.

Figure 36 shows the IA distributions for both the (a)LKG and (b)NLKG groupings. The IA values of both LKG and NLKG groupings follow similar distributions, with an IA > 0.5 in most cases for both train and test groupings. The median IA value for LKG groupings is 0.67, while the median IA value for NLKG groupings is 0.59. This indicates that the VAE is able to handle the higher variability of LKG groupings well. Regardless of LKG/NLKG classification, the train and test datasets follow almost identical IA distributions, with lower quartiles of 0.51 and 0.52 respectively, and both have a median of 0.61 and an upper quartile of 0.73. With less than 25% of the dataset having an IA value below 0.5, the VAE is verified as having sufficient reconstruction power. The LVs are, therefore, successful in providing sufficient information for reconstructing time-series data and showing the separation between LKG and NLKG classes. Given that, in this study, dimensionality is reduced from 96 points to a two-dimensional LV space, it is impressive that the VAE can produce LVs that sufficiently achieve both of these aims in only a two-dimensional LV space.



(A) (B)

FIGURE 36: THE IA DISTRIBUTIONS OF (A) LKG AND (B) NLKG GROUPINGS FOR BOTH TRAIN AND TEST SETS.

4.2.2.3 SVM

A radial basis kernel-based SVM binary classifier is trained on the mean LVs (μ_{LV_1} and μ_{LV_2}) obtained from the VAE using the training dataset. The SVM is trained to classify the mean LVs into LKG and NLKG accurately. Hence the LVs are the inputs to the SVM classifier, and the associated LKG/NLKG labels are the targets. The hyperplane and associated margins (ε) of the trained SVM are shown in the LV space in Figure 37. It can be observed that the hyperplane seeks to create the largest possible separation between the two classes of LKG and NLKG, with the margins largely covering the area of overlap between the two classes. Beyond these margins, only a few points are incorrectly classified.

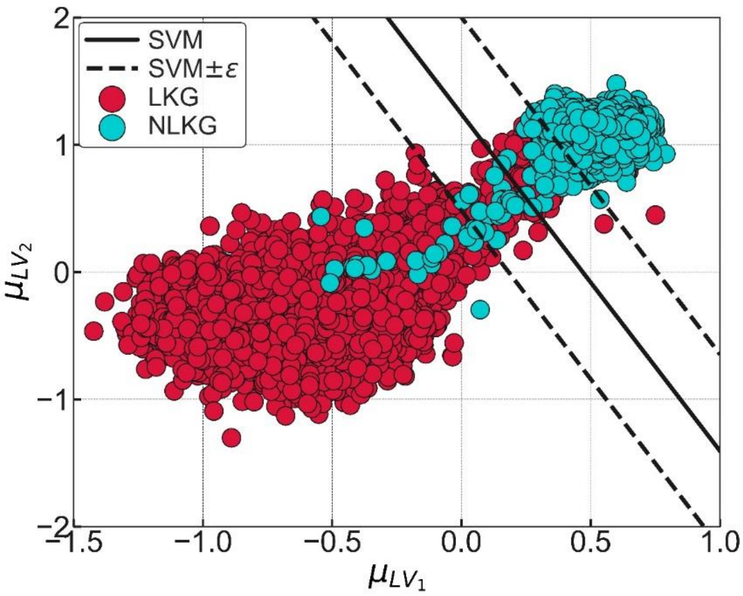
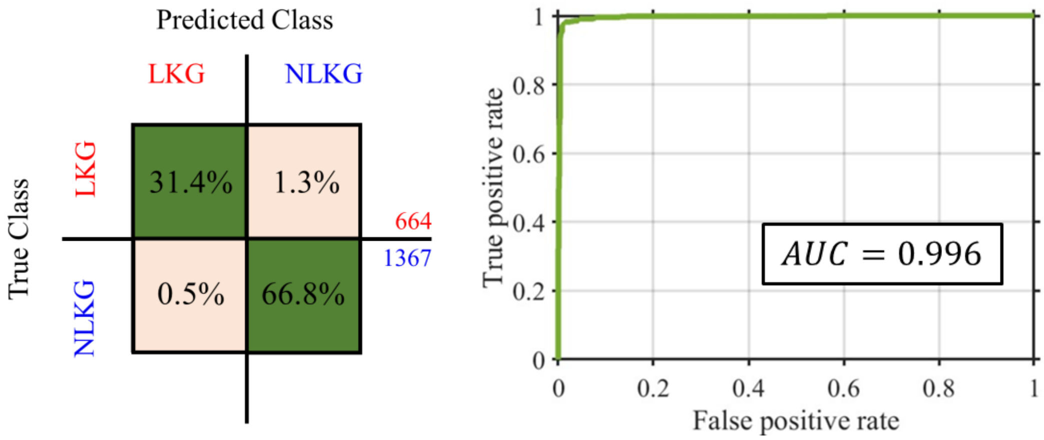


FIGURE 37: SVM HYPERPLANE AND MARGINS (ε) SHOWN IN LATENT VARIABLE SPACE.

The performance of the trained SVM is then tested on the test dataset. This dataset consists of μ_{LV_1} and μ_{LV_2} and their associated LKG/NLKG labels corresponding to the flow time-series in the test dataset (2,031 examples with two-thirds of NLKG and one-third of LKG data). The confusion matrix [591] and receiver operating characteristic (ROC) curve [592] of the classification results are presented in Figure 38a and Figure 38b respectively. It can be observed from Figure 38a that the SVM leads to an overall accuracy of 98.2% on the test set for classifying the LVs into LKG and NLKG classes. Furthermore, the SVM's precision (which is the fraction of LKG predictions in the LKG class) and the recall of the SVM (which is the fraction of all LKG LV inputs that are correctly predicted as LKG) are 98.3% and 95.9% respectively. An F1 score, which combines precision and recall into a single metric by calculating their harmonic mean, of 97.1% is achieved using the trained SVM.



(A) (B)

FIGURE 38: THE SVM (A) CONFUSION MATRIX (FOR THE 2031 POINTS IN THE TEST DATASET) AND (B) ROC CURVE FOR THE SVM CLASSIFIER, WITH $AUC = 0.996$.

The ROC represents a probability curve that provides a measure of how well a model can separate two classes. The area under the curve (AUC) indicates classification accuracy and can range from a minimum of zero to a maximum of one. Figure 38b shows the ROC-AUC curve for the trained SVM classifier. It can be observed that the SVM classifier leads to a high AUC value of 0.996, thereby indicating excellent classification power. Furthermore, the strong performance on the test dataset demonstrates that the SVM could be used to accurately classify any new, unlabelled time-series groupings as either LKG or NLKG, based on the mapping of the corresponding LVs onto the LV space.

4.2.2.4 Comparison with MNF index

To assess the performance of the proposed framework against a traditional leakage detection method, a simplified MNF analysis is conducted. While there is insufficient data available to carry out a comprehensive MNF analysis, there is precedence for using a simplified MNF metric based solely on flow data [493]. A simple MNF index finds the ratio of MNF for a given night to the mean or median of night flow over a preceding windowed period. High index values are more likely to represent abnormal flow events, which include leakage. The size of the window period varies in the literature from three days to six months [536] [593] [594] [595] [596], though it is generally agreed that a larger window can give a better representation of typical night flow behaviour for a given DMA. This study selects a window of seven days, as this covers a full week of flow data (including the weekend) yet is short enough that sufficient data is available for almost all groupings. Of the over 10,000 groupings in the combined train and test datasets, only 73 do not have a week of preceding flow data available. The nighttime hours used to calculate MNF also vary in literature, beginning as early as 12am and ending as late as 5am [593]. This study uses the hours of 2am to 4am, which are selected in existing studies [55]. To find the MNF index, the median value of flow during these hours (night flow, NF) over the window period is found. The median is chosen over the mean to limit the effects of any erroneous data, as MNF is sensitive to fluctuations or anomalies. For the night of interest, a significant deviation from this value during the same hours can be taken to indicate possible leakage under MNF analysis. This deviation is found using Equation (13), where d is the 24-hour day of interest and i is the size of the window period in days.

$$\text{MNF index} = \frac{\text{median}(\mathrm{NF}_d)}{\text{median}(\mathrm{NF}_{d-1}, \mathrm{NF}_{d-2}, \dots, \mathrm{NF}_{d-i})} \tag{13}$$

For purposes of comparison, this study defines an MNF index of 1.1 or greater, which represents >10% deviation from the median preceding NF, as indicative of potential leakage. This aligns with MNF index values seen in literature [493], but this threshold could be adjusted if necessary.

To assess the accuracy of this MNF index for leakage identification on the dataset used for this study, the train and test datasets are combined so that all ~10,000 LKG and NLKG groupings can be analysed. The 73 groupings that occur within the first week of the flow dataset, and thus do not have a week of preceding flow data available, are excluded. The confusion matrix of the classification results of the MNF index analysis is presented in Figure 39.

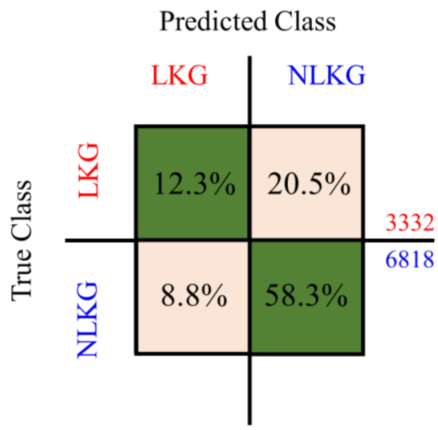


FIGURE 39: THE MNF CONFUSION MATRIX (FOR THE 10,150 POINTS IN THE COMBINED TRAIN AND TEST DATASETS).

Of the 10,000+ groupings, the MNF analysis accurately classifies 70.7%. While not an insignificant result, this does fail to match the accuracy of the proposed VAE-SVM framework on this dataset. The MNF analysis misclassifies a significant portion of LKG groups as NLKG (over 20% of the total groupings). An additional benefit of the framework over the MNF index is that the framework does not require a specific period of overnight flow. This allows the framework to identify possible leakage at any time of day, allowing for a more rapid identification.

4.2.3 Restoration process

4.2.3.1 Introduction

Based on discussion with a large UK water company, the present method for repairing leakages is far from optimal. Water companies recognise customer reported leakage, often termed 'visible' leakage, as both a greater priority and as easier to precisely locate than leakage identified based on data from the sensor network. Leakage identified through data analysis is dealt with through a series of steps. The first step often involves the sending of an exploratory team to the relevant DMA, with the aim of identifying the likely location of the leak within the DMA. This team feeds information back to the company, who then schedule a repair team based on the information provided by the exploratory team. The actual repair of the leaking component often involves road closures to enable a pit to be dug for access. Depending on the accuracy with which the exploratory team are able to locate the leak, the pit may need to be expanded or multiple pits dug to find the exact site of the leak. At present there is no recommendation for how leakage should be prioritised in England and Wales, although water loss is the metric used to measure leakage performance [71].

As this study does not have access to data at the component level, the restoration process is limited to the DMA level. As such, the results of this study provide a prioritised schedule that can be considered as a recommended list for the exploratory teams, rather than the repair crews themselves. However, as addressed in the review of work in this area, there exist several methods that could be applied to these results that can go beyond the DMA level to find the most likely pipes causing the leakage, in the event of access to additional data at the pipe level.

4.2.3.2 Prioritisation of leakage response

Table 8 shows the top 15 entries in the combined leakage detection and leakage forecasting output database, taken at the point of 00:00am of the 12th September 2016. The detected entries, shown in orange, cover the week leading up to this date and time, while the forecasted entries, indicated by purple, cover the upcoming week. The Z values are calculated for the forecasted groups using the mean flow forecast only, as residual forecasting is not available until after the outlier start point. As shown in the results of the anticipatory process, the fluctuation of forecasts tends to be distributed relatively evenly above and below the flow profile of the recorded outlier, indicating that Z values for forecasted leakages should not significantly overestimate or underestimate the actual leakage.

TABLE 8: COMBINED DETECTED (ORANGE) LEAKAGE EVENTS (5TH TO 11TH SEPTEMBER) AND PREDICTED (PURPLE) LEAKAGE EVENTS (12TH TO 18TH SEPTEMBER), SORTED BY Z VALUE – TOP 15 EVENTS.

DMA	Outlier Start	Outlier End	Z Value	DMA Repeat
1814	10/09/2016 03:00	10/09/2016 13:15	100.8195563	No
1719	14/09/2016 14:15	14/09/2016 20:15	41.47342	Yes
1167	09/09/2016 05:00	09/09/2016 14:15	39.16277964	Yes
547	17/09/2016 23:45	18/09/2016 09:15	38.96721	No
1378	14/09/2016 06:45	14/09/2016 15:00	36.30383	Yes
1719	17/09/2016 11:00	17/09/2016 17:45	30.37194	Yes
1719	13/09/2016 10:00	13/09/2016 20:00	29.01111	Yes
516	18/09/2016 23:45	19/09/2016 08:00	23.09285	No
1378	13/09/2016 06:00	13/09/2016 17:15	20.931	Yes
755	12/09/2016 13:45	12/09/2016 19:00	19.46047	No
790	13/09/2016 08:15	13/09/2016 13:00	19.20192	No
1167	11/09/2016 01:30	11/09/2016 06:45	19.11405242	Yes
1378	15/09/2016 06:00	15/09/2016 16:30	18.40204	Yes
1798	13/09/2016 06:45	13/09/2016 13:45	18.28456	No
1343	07/09/2016 13:15	07/09/2016 18:30	16.9443104	No

Interestingly, of the top 15 entries, only four are provided by outputs of the detection process, with the remaining 11 coming from the prediction modelling. The top entry, with a Z value over double that of the following entry, however, is a detected leakage. This indicates that both the detection and forecasted data are integral to effective leakage management, and that many of the most severe bursts can be anticipated and, with sufficient resources, potentially averted. It also shows that Z values for forecasted data fall within the range seen in detected data, so the two outputs can be combined into a single database that does not neglect either component in favour of the other.

Within the top 15 entries, there are three DMA IDs that appear multiple times. This may be indicative of a single leakage event being flagged multiple times if it has not been repaired. This may be the case for DMA 1167, for example, which appears three times as a detected leakage entry, as there is no logged repair for the dates between these entries. For the forecasted events, repeated entries should be treated with care here, as in reality each forecast would be updated as time passes into the period in question and the entry would, should potential leakage be detected, be replaced with a detected entry. If this triggers a repair event, it would likely have resolved the leakage issue and mean that leakage flow is unlikely to be forecast, so the repeated forecasted entries would be averted. This could explain why there is a greater proportion of forecasted entries in Table 8, but this may not be the case in a live system. Entries of repeated DMA IDs in forecasted data, therefore, can perhaps be thought of as a stronger warning that leakage is expected in a given DMA, as multiple occurrences are less likely to be other anomalies, and so these could perhaps be given even greater priority in repair scheduling or monitored more closely to see if leakages are indeed later detected. This would be up to the discretion of the operator and is currently beyond the scope of this study.

Based on the entries in Table 8, and taking the severity of leakage as the single criterion for repair priority, a list of DMAs is presented in Table 9. This list represents the DMAs that should be attended by exploratory crews (with a view to repairing the leak) and the order in which they should be prioritised. Also included in Table 9 is the total number of properties in each of the DMAs. Without knowledge of additional pipe properties, further localisation of the suspected leakage is beyond the scope of this study. However, it can be assumed that the localisation of leakage that is not visible at surface level will take longer in DMAs with a greater number of components, which correspond strongly to the number of properties served. Based on the limited data available on the characteristics of DMAs, it can be expected that, from Table 9, a leak in DMA 1719 (which serves 60 properties) will be located more rapidly than a leak in DMA 1167 (which serves close to 800 properties).

Precise location data is not available for each DMA in this study, but this could be an additional criteria that operators may wish to consider, as time taken by repair crews to drive between locations is a factor in optimising repair scheduling. There are other factors, including type of properties served, land access, and the quantity of repair equipment and crews available, that should be considered by water companies if using these results to develop a repair schedule. Additional constraints for inclusion or continued inclusion in the repair schedule may be added based on budget constraints.

TABLE 9: .PRIORITISED LIST OF DMAS FOR LEAKAGE EXPLORATION TEAMS, WITH CORRESPONDING PROPERTY NUMBERS FOR EACH DMA.

DMA	Total no. of properties
1814	413
1719	60
1167	789
547	474
1378	71
516	164
755	147
790	86
1798	104
1343	231

5 DISCUSSION

5.1 INVESTIGATION PROCESS

The design and execution of this research was far from linear. The self-healing approach, as applied to infrastructure systems, is still evolving and findings its feet in academic research and even more so in industry. Underlying terminology and concepts are inconsistent across infrastructure sectors, and largely absent from many. With this in mind, the process of conducting this investigation was highly iterative. While self-healing represents the core of this study, exploration of AI as a supporting field was found to be highly significant and offers its own unique insights into cross-sectoral approaches to AI in infrastructure systems. At each stage of the research process, the implication of findings for earlier stages of the process were considered and frameworks and methods were updated appropriately. The research process is presented in Figure 40.

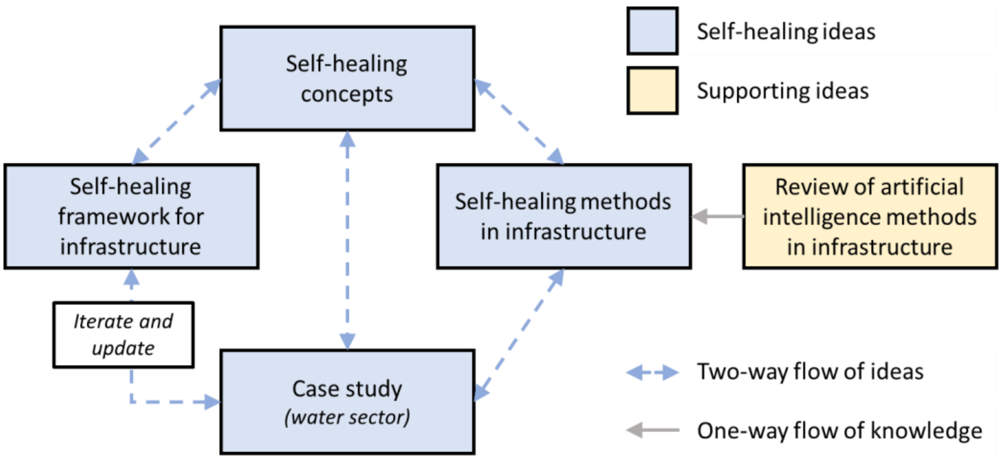


FIGURE 40: DIAGRAM OF THE RESEARCH PROCESS.

5.2 IMPLEMENTATION OF SELF-HEALING IN INFRASTRUCTURE SYSTEMS

5.2.1 SELF-HEALING FRAMEWORK FOR INFRASTRUCTURE SYSTEMS

Exploration of the concepts found in the limited literature on self-healing in infrastructure systems has informed the development of an updated self-healing framework for the management of infrastructure systems, illustrated in Figure 41. This framework seeks to maintain the generality of the initial self-healing framework presented in section 1.1, while adding additional descriptions to capture the key aims of each process. The adapted state and the processes connected to this state are added and developed, to recognise the complexity and diversity of the restoration of critical infrastructure systems.

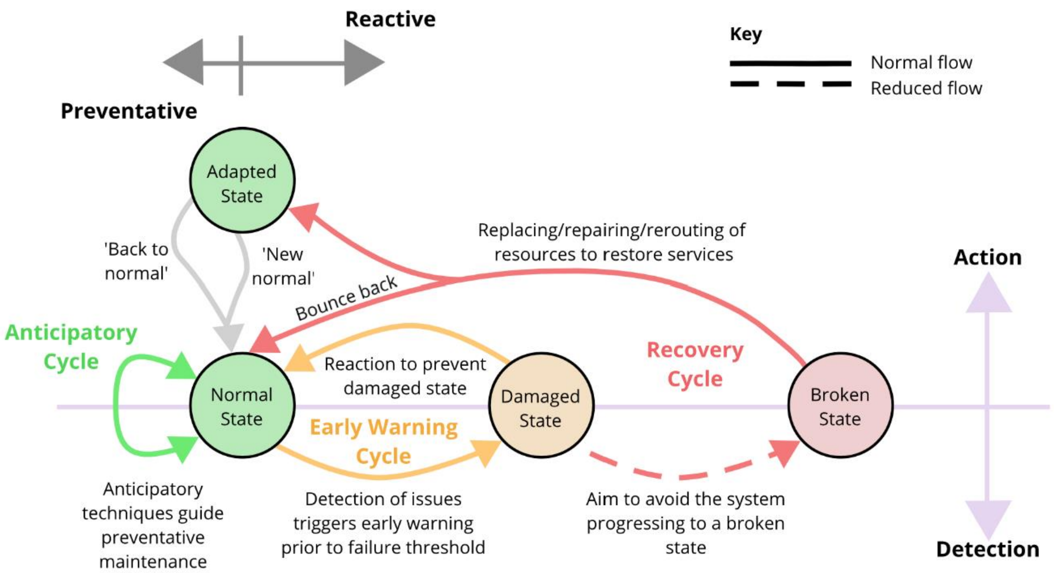


FIGURE 41: A SELF-HEALING FRAMEWORK FOR INFRASTRUCTURE SYSTEMS.

While the initial theory of self-healing software systems proposes three states [13] – normal, damaged, and broken – it was quickly identified that, in infrastructure systems, a case can be made for a fourth ‘adapted’ state. This is due to the wide range of restoration approaches that can be applied to infrastructure systems. There are many factors that go into decisions regarding the repair of infrastructure assets, including the urgency of the repair and the accessibility of the damaged component. It can be the case that, in order to achieve acceptable service, a temporary or alternative solution is adopted. This may or may not include the repair of the damaged component but can be considered a restorative action in the system if it results in acceptable service being restored. The transition from the adapted to the normal state can happen via one of two pathways. One pathway is the ‘back to normal’ pathway, which sees the damaged system eventually restored to its original state, but with some temporary support in place to provide a degree of operationality in the meantime. One example of this would be the use of mobile drone-mounted base stations to restore wireless network access in post-disaster scenarios [597]. This is an adapted and, in this case, a temporary solution that restores the functionality of the wireless network but the system is not (yet) returned to the pre-damaged set-up. Once time and resources are available to repair the damaged network, the mobile base stations can be removed and the system is ‘back to normal’.

Adapted states may not necessarily be the result of a disaster scenario or be temporary. Indeed, they may represent an improved state. The ‘new normal’ pathway indicates that the adapted solution has been adopted as a permanent solution. This may be due to budget limitations or an inability to restore the original infrastructure system setup, or it may be due to the adapted state being better in terms of performance, feasibility, or cost. An example of this is rainwater harvesting as a solution to unreliable water supplies. While rainwater harvesting can present a temporary emergency solution when water supplies are disrupted by disasters (including earthquakes and droughts), it is also recognised as a long-term option for decentralised water supply in areas with unreliable access to a centralised system [598]. Rainwater harvesting can also cut emissions from water supply and distribution systems and mitigate flood risk. Implementing rainwater harvesting systems in communities that receive sufficient rainfall can mitigate the impacts of poor or unreliable water supplies, and adopting this solution on a permanent basis makes these communities more resilient to disruptions to their water supplies [599].

Adapted solutions may also incorporate new technology that was not available during construction of the initial system. For example, it may be economically unfeasible to upgrade assets such as buried pipelines while they are still in service. However, should breakage or leakage occur that requires replacement components, and thus a costly excavation, it can be prudent to take the opportunity to replace assets with more up-to-date components, such as including new sensing technology or using more advanced materials. In this case, the adapted state would eventually, once rolled out across enough of the network, become the new normal state.

The updated framework also includes defined cycles, which represent a route for maintaining or restoring the normal state. The anticipatory cycle seeks to keep the system at a healthy state without any degradation, and thus requires the system to have self-awareness through detection and to make proactive interventions such as preventative maintenance. The early-warning cycle represents the transition to a degraded state and subsequent restoration to normal, without crossing a defined failure threshold. Again, this requires the system to be aware of its present state. This cycle also requires the system to trigger actions that return the system to a normal state which, given that some degradation has occurred, may require some degree of human intervention. Finally, the recovery cycle sees the system go from normal to broken and then back again, restoring service provision after a failure threshold has been crossed. Here, reactive interventions are necessary, which often require additional information on repair equipment and personnel for effective implementation. While all three cycles require a foundation of system self-awareness through detection, they often vary in the types of action necessary to maintain or restore a healthy, normal state. Examples of actions in the anticipatory cycle include preventative maintenance and operational control processes, while actions undertaken as part of the early-warning cycle may include provision of additional capacity or demand reduction strategies such as hosepipe bans in water systems. Finally, the recovery cycle may require the repair of broken components in the infrastructure system, or the rerouting of flows around a broken component. It should be noted that the early-warning cycle and recovery cycle may share some common actions, depending on the failure threshold defined for a given system.

There are a variety of reactive action types that can help to restore operationality in infrastructure systems. Based on exploration of the relevant literature, it is found that these can be broken down into four main categories;

- **Repair**. The process of repair involves fixing broken components or installing new components in place of broken ones on a like-for-like basis. If improved versions of the component are available (newer materials etc.), these may be used in the repair in place of the existing component specifications. An example of repair is addressing leakage in water pipes by installing new pipes in place of the leaking pipes.
- **Replace**. Replacement finds an alternative method for providing the same service. Replacement is different from repair in that the replacement is substantially different from the original method of service provision. Replacements can be temporary solutions, such as the use of a replacement bus service for tube or rail routes that are out of service.
- **Reroute**. Rerouting involves redirecting the flows within the system around failed components so that as many customers can access services as possible. If a system has sufficient redundancies, effective rerouting may allow service to be restored to a normal level. Telecommunications systems provide many examples of rerouting,

with traffic redirected to ensure that data can still reach its intended destination even if certain network segments or nodes fail.

- **Reorientate**. A relatively new term in the context of resilience of infrastructure systems, reorientation considers that the original purpose or service of a system may no longer be valid or sufficient under changing circumstances or disruptive events. Reorientation acknowledges that, in the face of unexpected challenges, an infrastructure system may need to adapt and evolve to fulfil different or additional functions to effectively serve the needs of its users or stakeholders. An example of reorientation is the decentralisation of energy infrastructure via household-level solar panels.

5.2.2 Self-healing framework applied to water systems

During the literature review of self-healing in the water sector specifically, as well as in the development of the water sector-based case study presented in section 4, it was noted that the existing research in this sector does not always align with the cycles presented in Figure 41. This may be due, to some extent, to the lack of self-healing approaches in the water sector and the siloed nature of much of the existing work on the management of water infrastructure. The developed self-healing framework is thus adjusted to better reflect how self-healing might be approached in applications in the water sector, with a framework that aligns specifically to the developed case study presented in Figure 42. The individual flows and states remain identical across both imaginings of the framework, but each version groups together different flows within the system, with Figure 41 giving three cycles and Figure 42 giving three slightly different processes – anticipatory, detection, and restoration. These align with the processes presented in the case study. This modified framework is not intended to replace the more generic framework of Figure 41 but instead to show how processes within Figure 41 better align with existing research in the water sector and leakage management specifically. As this version is informed not only by the literature in the water sector but by the pipe leakage case study of section 4, it could be considered an application of the generic self-healing framework to the specific task of leakage management. It may be that this version of the framework aligns with other sectors or purposes, but this would have to be verified on a case by case basis. It should be noted that leakage management, as described in the case study, represents an example of 'repair' as a reactive action. It may be that alternative types of reactive actions – replace, reroute, reorientate – are better suited to the original cycles shown in Figure 41, or to a different perspective on the self-healing processes altogether.

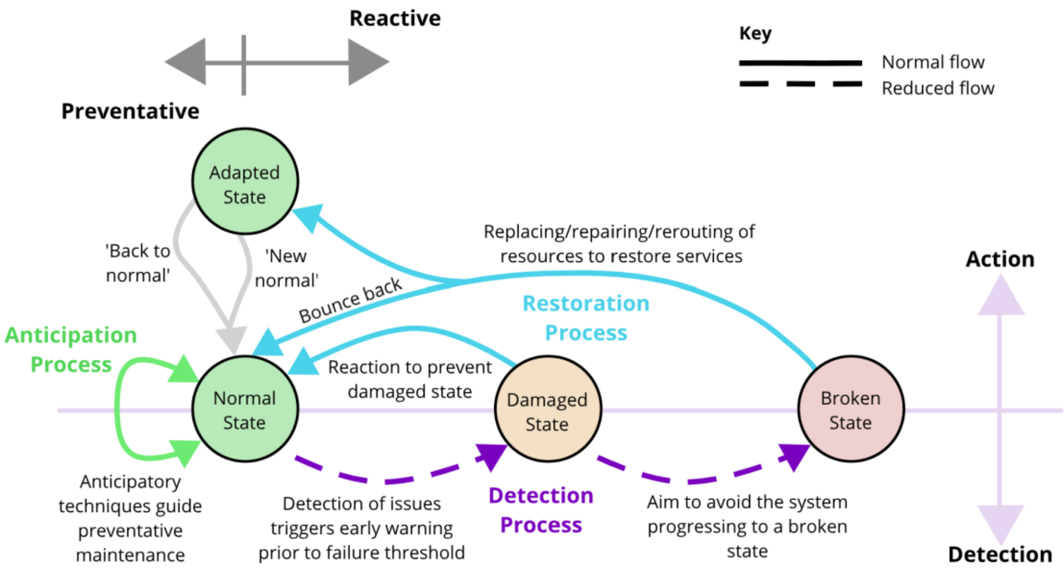


FIGURE 42: THE SELF-HEALING FRAMEWORK AS APPLIED TO THE CASE STUDY OF LEAKAGE MANAGEMENT.

5.2.3 CONSIDERATIONS FOR IMPLEMENTATION IN THE WATER SECTOR

5.2.3.1 From siloed to systems-based solutions

As introduced in section 2, perhaps the greatest barrier to implementation of a self-healing based approach in the water sector is the current status-quo of a fragmented and siloed approach to water network management. In England, where the case study selected for this research is located, water supply is vertically integrated with sewage services and has been fully privatised since the 1980s. This means that privately operated water companies are responsible for water management in different regions of England. While other network industries (e.g. electricity, telecoms) have been subject to 'vertical unbundling' with the goal of driving competition, water remains vertically integrated. This means that, in a given area, one company is responsible for getting water from 'source to tap'. Both vertical integration and vertical unbundling have their limitations in terms of developing a true systems-based approach to network management. Vertical integration should allow for better data transfer and management between sections of water management services, with the same company responsible for water supply, distribution, and wastewater management. The division of responsibility across regions, however, can prevent the emergence of a common best practice or shared knowledge and expertise. It is only if water companies communicate effectively, both in terms of expertise and data, can a shift towards systemic approaches occur successfully. In the last few years, the call for better communication between water companies has grown louder [600]. It is recognised that, with data at the heart of modern water system management, it is only through sharing data and insights generated from it that water companies can accelerate the transition from their current, siloed approaches, to improved systems-based methods. Sharing of information offers numerous benefits, including greater training data for new models and the ability to learn from trials of new technologies and methods by other companies to improve implementation.

5.2.3.2 Data management

At the level of individual water companies, there must also be efforts to improve the fragmented approaches to data management. An explicit information architecture should be established in order to facilitate effective data sharing, in combination with a reliable and often-updated asset database. A first step for many companies may be establishing an up-to-date asset database, which is itself challenging given the aging state of the UK's water infrastructure. These formalised data structures are crucial in enabling existing techniques to come together into a wider system, as data formatting and completeness may vary between teams managing different sections of the water network. A more systemic approach to data management would see the standardisation of data collection and recording, but the development of and transition to an approach would take time. Therefore, incorporating flexibility into methods through a pre-processing stage will assist in the integration of different datasets. There may be a need to retrain staff or bring on new hires in order to develop or update these data systems and ensure all relevant staff are able to use them effectively. New models that can support a self-healing-based approach should be provided with access to relevant data so that they can be developed with the data format in mind. Integrating data such as pipe locations and properties with data on available repair equipment and crew availability could allow for the combination of many existing methods that could currently be considered decision support tools into a greater self-healing framework that would instead produce a self-managing or assisted-healing system.

5.2.3.3 New technologies

New technologies are coming to the market in the water sector that offer new potential in areas such as burst detection and pipe repair. As a network with many underground assets and a significant amount of aged infrastructure, the water sector faces more barriers than many other infrastructure sectors when it comes to the implementation of a fully self-healing approach. One field that may bridge the final gap between an assisted-healing or self-managing system (with a human-in-the-loop responsible for digging up and repairing/replacing a pipe) and a true self-healing system (with the pipe able to be repaired by the technology itself) is in-pipe robotics [601]. Although still in the research and development stage, this technology should be monitored and supported by water companies. While the existing setup of water systems may not allow for the repair of pipes without human involvement, a self-managing system would take all but the most physical tasks out of the hands of the operator and make them the responsibility of the system. This has the potential to significantly improve the efficiency of operations by optimising complex problems such as leakage detection and multi-objective repair scheduling.

5.2.4 Limitations

The main limitation of the self-healing framework proposed in this research is that the application of this framework may look very different across sectors and purposes. The ways in which the individual transitions between states are grouped may change depending on the specific application. The framework is designed to allow this flexibility, but there is a degree of research and application-specific expertise necessary to effectively align the framework to a given application if successful implementation for an existing system is the goal. Aligning the framework in such a way that existing techniques can be substituted into processes or cycles gives the best possible chance of the framework being adopted successfully in a real-world system.

This research presents a general framework for self-healing in infrastructure systems, but the framework is demonstrated on a single case study, which focuses on the specific application of the framework to leakage management. The framework is not validated on other types of infrastructure system, which may present different or unexpected challenges.

5.2.5 Further work

Future research should seek to develop the framework further across a range of different infrastructure systems. These systems may follow same processes as the case study in section 4 (see Figure 42), may follow the cycles shown in Figure 41, or may require the defining of entirely new processes within the self-healing framework.

Different reactive actions and their impact on the restoration process should be considered. For example, rerouting as a reactive action may require the framework to be implemented with different structures or processes than repair or replacement. Case studies should be selected and developed that consider a range of reactive actions, as well as examples of an adapted state.

Additional case studies should be developed and tested to explore systems in different infrastructure sectors such as energy, transport, and telecommunications. Interconnected systems and systems that sit at the overlap between sectors should be given particular consideration. Figure 43 shows the data flows in a leakage management system. As systems with greater levels of interconnectivity are considered, the complexity of data flows and associated data management will only grow. Future work must consider the challenges of data integration and standardisation to a greater degree. This should include consideration of how different data streams can be integrated into a self-healing approach when data is stored in different locations, in different formats, and has different data security requirements.

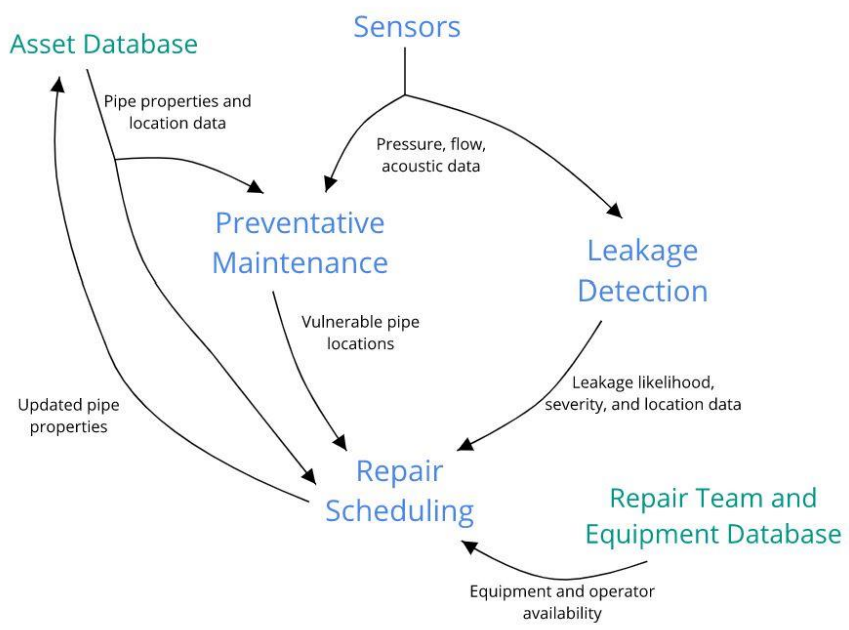


FIGURE 43: INFORMATION FLOWS IN LEAKAGE MANAGEMENT SYSTEM.

It is important that future work look at how the framework can be applied in practice for different types of failure – e.g. different hazards such as earthquakes or cyberattacks. It is necessary to consider how the framework would work for a system facing multiple hazards. It may be that failure thresholds are defined in terms of service provision, which is independent of the failure cause, but that reactive actions must be defined in terms of hazard-specific actions. It may instead be necessary to consider different failure thresholds based on different hazards. The chosen approach may depend on the type and availability of data from the system.

Finally, the application of the framework to systems with low levels of data sophistication should be considered in future work. Regions with limited economic means, or geographically isolated areas with decentralised systems, may have much less available data. As the framework does not prescribe specific methods, it is hoped that it would still prove to be relevant and effective for such systems. However, whether AI remains an appropriate enabler is less clear. Future work could look at the effectiveness of AI approaches (in comparison with alternatives such as expert-informed rules-based methods) in enabling self-healing in systems with low data availability and/or poor data quality.

5.3 CASE STUDY

5.3.1 INTRODUCTION

The case study presented in chapter four offers insight into how machine learning could deliver some of the processes necessary for a self-healing approach to managing failures in a real-world infrastructure system. It also helps to illustrate some of the challenges and limitations of implementing such an approach.

The following sections discusses the various insights from the results of the case study, consider the feasibility of implementing the proposed methods in an operational capacity, detail limitations of this case study, and suggest areas for future research. This discussion goes beyond the specifics of the leakage management case study to consider the rapidly evolving AI landscape and how this may impact the way consumers, and the public in general, interact with AI technologies in the context of infrastructure systems.

5.3.2 The future of AI in infrastructure systems

The machine learning-based methods demonstrated in this study illustrate the value of machine learning as an enabler of self-healing. The underlying principles of self-healing include that a system is able to 'know' its own state and anticipate deviation from a healthy state. These dovetail well with the abilities of machine learning tools. If built into an appropriate architecture that includes pre-processing of data if necessary (as it was in this case), machine learning methods show huge potential in delivering the insights necessary for self-healing.

Machine learning methods, to reach this potential, need to be designed to consider the specific application to which they are applied. While 'off the shelf' models may be sufficient for some applications, the complexity of critical infrastructure systems necessitates a more tailored approach. The detection framework proposed in this study, for example. includes training of a domain-informed VAE that utilises a novel loss function developed with the domain-specific knowledge that leakage and non-leakage flow possess different characteristics, as seen in Figure 22. Thus, the use of machine learning methods for self-healing in water networks should be seen not just as another application of AI but instead as an opportunity to integrate knowledge of the water sector into machine learning tools to tailor these techniques to achieve the best performance for the specific application.

However, machine learning alone is insufficient to significantly transition from DSS to true self-healing. The former are designed to aid human operators, while the latter are designed to make decisions in complex systems without the need for human operators. The key difference is therefore who or what makes the decisions in the system in standard operational conditions. The line between these two becomes blurry when the operational reality is that, for many systems, a human operator remains involved to varying degrees across various system components. And indeed, some degree of human oversight is very valuable in critical infrastructure systems, as human override capacity builds system resilience and reassures users [40]. While self-healing systems evolve, and while many infrastructure systems remain reliant on human operators to carry out restoration processes, this close similarity in DSS and self-healing is likely to remain. For this reason, future research and development into self-healing infrastructure systems, particularly those without self-healing terminology in their standard operational lexicon, should look to existing work on DSS for insight into the progress made thus far. To see a shift from DSS to self-healing, there needs to be a greater trust in AI-based systems, which can only be developed through demonstrating effective and reliable performance results.

The AI subfield of robotics, which is often underpinned by machine learning methods, may offer a solution to the final hurdle that is presently keeping leakage management at an assisted-healing or self-managing level rather than true self-healing. The potential of in-pipe robotics is discussed in section 5.2.3.3.

Initially, it was expected that a self-healing system would represent a closed unit, with overarching methods underpinning the entire system. However, in the initial review of the concept of self-healing systems, it became apparent that there were several underlying processes that made up the larger self-healing system, these being represented by the anticipatory, detection, and restoration processes in this case study. It was also evident that much of the existing research in relation to the management of systems in the water section could be aligned with at least one of these processes, but very few considered all three of the processes necessary to constitute a full self-healing system. It was also apparent that, as long as inputs and outputs follow a consistent data format, outputs from each process could flow into another as an input. This is a particularly positive insight as this means that many of the existing methods found in literature on the topics of flow forecasting, leakage detection, and repair prioritisation can, with sufficient pre-processing and post-processing of data, be adapted to fit into a broader self-healing framework. This is also hugely significant for implementation of the framework, as water companies will be able to switch out any of the proposed methods for alternatives that they are currently using if they so desire. This would potentially allow for a more staggered transition; first the existing methods used by a company are integrated into a self-healing framework and then new or improved methods are substituted in for the older ones. For example, MNF could be used as the method for leakage detection if that is appropriate level of maturity for a particular operator. This could allow for a more gradual building of both skills and trust in the proposed approach, before more complex methods are introduced. The transition to more sophisticated methods can be done in a gradual manner, without the need for a complete overhaul of initial operating practices. As operators are trained in relevant skills and more advanced computing capabilities are established, the company may then be in a position to substitute more complex methods into a given process of the self-healing framework.

The AI landscape is rapidly evolving. Not only are companies and operators changing how they utilise AI, but the relationship between the public and AI has been transformed with the created and rollout of AI foundation models including ChatGPT, DALL-E etc. [602]. The public is more aware than ever of the potential of AI (natural language processing and machine learning in particular) and are seeing examples of how AI-based tools can impact their daily lives and change longstanding behaviours. This opens up many new opportunities to integrate AI into public-facing elements of infrastructure systems, which may help to shift the relationship between suppliers and consumers from a one-way flow of supply to a two-way collaborative approach [603]. An example of this applying machine learning methods to smart meter data to identify patterns in consumer behaviour at the household level and using natural language generation to deliver tailored advice on how to reduce consumption. This has begun to be explored to a limited extent in an energy context [604], but as the water sector begins their smart meter rollout it is likely they will learn from AI interventions deployed in other sectors. As a sector where consumers have typically been very detached from their suppliers – consumers cannot choose who supplies their water and before smart metering often paid based on number of people in a household rather than based on actual usage – the potential of these methods to prompt people to interact with their supply and consider their consumption may bring huge transformation in how the public both perceive and interact with their water supply.

5.3.2 Feasibility and implementation

5.3.3.1 Introduction

Discussed in this section are some of the issues that, based on the literature in this field and conversations with industry professionals, may need to be given further consideration if the proposed case study methods and frameworks are to be successfully implemented in real-world water distribution systems. This is not intended to be an exhaustive list, but to address some of the most significant potential feasibility concerns and barriers to implementation.

5.3.3.2 Data considerations

As the proposed framework is developed using historical data with some restrictions, there are associated uncertainties such as how representative the data is of current demand behaviours and whether assumptions regarding repairs are true to life. If the proposed system was to be adopted for commercial use, there are several hyperparameters that can be edited by those with expert knowledge who work for the interested water company (as ideal values may vary between regions/water companies). These include the minimum required length of outlier period to be classified as potential leakage and the minimum required length of flow data preceding an outlier. It can also be assumed that, if adapted for commercial use, there would be additional data available that could improve the accuracy and efficiency of the proposed system. For example, having more detailed information for each entry in the repair log would provide a far more reliable basis upon which to compare outliers with known leakage. There may well be additional pre-processing associated with this, such as filtering out of any non-leakage related repairs. In the long term, after the system has been operational for a substantial period of time, it may no longer be necessary to use historical repair records as there may be a sufficient number of confirmed leakages while the system is connected live network. This would improve the accuracy of leakage detection and forecasting by ensuring that the training sample contains only true leakages. It would also simplify the pre-processing stage.

5.3.3.3 Time-series frequency

In order to operate most effectively, the proposed system assumes access to near real-time updates from flow sensors (every 15 minutes in this instance). This is particularly true of the forecasting process, which updates using residual forecasting at each timestep. Successful implementation would see the system provided with this regularity of update. How this would work is down to the technical capabilities of a given water company and their approach data collection and collation. If any data needs to be withheld from the system, for example for consumer privacy reasons, this could further complicate the near real-time link, as this data would either have to be removed being the data is sent to the system or stored separately from the shared data. A better understanding of the existing data architecture of a given water company would therefore be necessary in order to facilitate the smooth implementation of the proposed system. There may also be some changes necessary to the pre-processing stage of the proposed system, depending on both the specific data formatting choices of the water company and their existing sensor setup.

5.3.3.4 Technical feasibility

The feasibility of solutions is concerned with any potential barriers to effective implementation. One key consideration is whether the current technology available to water companies is sufficient to provide the necessary data to the proposed framework. While novel sensor technologies may offer some improvements in accuracy or precision, not only does their rollout take significant time and require significant investment but there is a need to build up a database of historical data from these new technologies in order to ensure a representative sample is available to train models. The frameworks proposed in this case study are demonstrated on a dataset of flow time series data. While they could be easily adapted to work with other time series data, the benefits of using a sensor type that currently offers widespread coverage across a network are huge. The proposed methods can be implemented immediately, as sufficient training data is already available, and across the entire network, rather than just in the limited areas where new sensor technologies are deployed.

Whether a solution is feasible also depends on the required computing power and the cost of implementation. Cost here can include necessary upgrades to computing power or data storage capacity, as well as the costs of training individuals in how to use the required software. There may also be costs associated with converting existing databases into the required format. These factors should be explored if the proposed solutions are to be commercialised. Hyperparameter tuning is one element of the proposed methods that can require some time investment upfront, but this should allow the models to run more efficiently once operational.

5.3.3.5 Operating culture and pressures

However, factors that impact feasibility extend beyond the issues stated above to include workplace culture and operating priorities. There may be training needed in how to implement and interpret the proposed methods, and operators may well need to see results to be convinced of their efficacy. This is particularly true for the forecasting element of the proposed approach, as this is a less well-established field and likely one that has been unexploited by water companies before now. It may be that operators do not feel equal weight should be given to forecasted and detected leakages, with priority instead given to the latter. If forecasting proves very effective in reducing overall leakage, this could build confidence in this method. However, there may be limited resources available and water companies may wish to prioritise leakage that has already occurred as is presently impacting customers. It is only by giving the forecasting component a chance in an operational setting that it's true value can be known, and so it is hoped that, if the method is adopted in industry, water companies would be willing to at least trial a period of factoring forecasted leakage into repair prioritisation.

There must also be thought given to the weight of political pressures on operating priorities. In the water sector, significant public attention is garnered by short-term crisis incidents. Examples of such incidents include the discharge of sewage into public beaches during periods of heavy rainfall, and the introduction of hosepipe bans during extended periods of low rainfall. These issues understandably provoke a public response, with increased pressure on water companies and growing public distrust. These pressures can result in the shifting of investments or resources to address the issue that is drawing negative attention to the sector at the time. This may limit the ability of water companies to invest in implementing the proposed method, or it may result in greater resources available for the purpose of leakage management. Ofwat has committed to driving down leakage in the water sector in England and Wales, and so it is hoped that this will remain a priority even if other challenges are present in the sector.

5.3.4 Limitations

5.3.4.1 Introduction

The case study detailed in section 4 is intended to demonstrate the how, using AI methods, a self-healing approach might be applied to a real infrastructure system. With implementation and real-world feasibility, particularly from a technical perspective, in mind, it was decided that this case study should use data from a real-world system (albeit historical data). However, this choice and other necessary decisions regarding the scope and scale of the work introduce several limitations to the case study, the most significant of which are discussed in this section.

5.3.4.2 Data

Access to detailed data is a limitation of this study. While data for over 2,000 DMAs is provided, representing a very large area, the data is at the DMA level, and thus the proposed framework can only identify leakage at the DMA level. If this was to be extended to include localisation of leakage to an area within a DMA, or even at pipe level, additional details would be required. These could include pipe properties, land use, and soil properties. For the greatest accuracy in localisation of leakage, the ability to deploy additional sensors would also be beneficial.

There were further limitations in what could be inferred from the available repair logs, which gave only the DMA and date of repair. For better matching of outliers and repairs, it would be helpful to have the specific time of each repair. The repair logs did not give any reasons for an entry, and so while it is assumed that each entry corresponded to the repair of a burst, this may not have been the case. Due to customer data protection regulations, there was also no information on whether repairs are the result of consumers reporting visible leakage or the water company detecting bursts themselves. This information could inform what is set as a reasonable lag between outlier and repair. Additionally, if the study was to be expanded to explore leakage at the pipe level, repair data would also need to include details of the individual pipes/components repaired.

The data provided for this study was historical data, from April 1st 2016 to the same date in 2017. This means that models were training on flow data that represents typical demand behaviour during this time. These records predate the COVID-19 pandemic, which saw a widespread shift from in-office working to at-home working during lockdowns and left a legacy of normalised hybrid-working patterns. This is likely to have impacted water demand behaviours, and it would be expected that new patterns could be seen in typical daily water use. If more recent data is made available, it would be valuable to assess the differences between new and old datasets and to retrain the models on newer data.

5.3.4.3 Sensors

The methods proposed in this study assume a single type of sensor data, in this case flow data. While methods could be fairly easily adapted for different types of time series data, combining data from multiple sensor types into a single model would require further adaptation still. While water companies are overseeing the rollout of new sensor technologies such as acoustic loggers, it will be a long time before this extends to include all legacy infrastructure. During this transitional stage, with new technologies covering a limited area of the water network, there is a case for developing the methods used in this study to incorporate multiple sensor types with different extents of coverage.

The type of sensor (flow) also limited selection of methods for this study. While flow sensors are widespread across the existing water network, ensuring the proposed methods can be implemented without the cost of widespread upgrades to the sensing network, flow data can be less precise than other methods, such as acoustic loggers, when it comes to detecting leakages. Flow data also cannot offer obvious insight into how far a burst has occurred from the sensor, while the vibrations detected by acoustic loggers can change (depending on pipe properties) with distance from a burst. Pressure data may also have provided additional insight, but was not available for this study. Of the data provided, some flow data was incomplete, so techniques were needed for dealing with missing data.

5.3.4.4 Background Leakage

Existing methods in the field of leakage management often identify leakage by detecting a deviation from the 'normal' state. These methods therefore target new bursts, as opposed to background leakage. As data is not available for target or installation flow rates, this study is also limited to the identification of new bursts, neglecting background leakage. That is not to say that this study does not potentially capture some degree of background leakage in its leakage detection, as isolation forest may pick up outliers that are a result of slowly increasing flow rather than just sharp rises, but it is not the intent of this study to explicitly target background leakage. Indeed, any leakage that had begun before the start of the historical data used in this study and gone undetected is unlikely to be picked up by the methods used in this study. The methods to forecast leakage may be able to be adapted to incorporate background leakage, but would need additional data such as pipe parameters and significant repair data.

5.3.4.5 Geography

This study uses a case study of over 2,000 DMAs in a particular region of the UK, which are managed by a single water company. While the use of DMAs as a way of breaking down the water network into sections for leakage management is the standard across the UK, and has begun to spread to other countries, there are many places which use different methods. In areas with decentralised water management, there may be no established methods for dividing up the water network at a regional or national level. The ways in which subsections of a decentralised water network are managed are likely to vary significantly, as is the quantity, if any, and type of sensors used. Therefore, differences in sensor types, regulations, and water management may limit the applications of this study to countries with a sufficient level of coverage.

Even within the UK, it should not be assumed that water demand behaviour is homogenous. There are many factors that have the potential to influence water use patterns, including property information and population demographics. What is typical demand behaviour in the study area may well be different from other parts of the UK. If these methods were to be applied to another area of the UK, the models should be retrained on historical data provided by the relevant water company responsible for that area, so that the training samples are representative.

Finally, demand behaviour within the study area may not necessarily be homogenous. While it may be sufficient to assume that DMAs exhibit similar enough flow characteristics that frameworks can be trained on data from numerous DMAs, there may be specific cases of DMAs with atypical characteristics. Should unusual results be present for a particular DMA, it could be worth looking at variables such as the property type ('household'/'non-household') ratio to see if this offers a possible explanation for differences.

5.3.5 Further work

The restoration process of this case study uses a simple methodology and further work might want to develop this part of the study to present a more sophisticated framework for the restoration process. The chosen methods would likely depend on access to data regarding the pipe network and repair assets, but genetic algorithms and reinforcement learning methods show good potential in this field [577] [573].

The restoration component of this case study could also be expanded to include consideration of interdependencies with other infrastructure networks. For example, excavation to expose and repair a leaking pipe often causes road closures. If data from transport networks could be accessed and incorporated into the model, multi-objective repair scheduling could include minimising road closures or road user disruption.

This case study focuses on leakage management at the DMA level, based on the available data. However, provided more asset data is made available, the study could be extended to include a leakage localisation component within the DMA. This would further guide exploratory crews to the areas or pipe locations most likely to be responsible for the detected or forecasted leakage. Graph neural networks offer a lot of potential as a method for localisation in a network [605]. If data at the asset level is known, the study could also be extended to include a preventative maintenance database, which would dovetail with the anticipatory process to develop a targeted preventative maintenance strategy for pipe replacement based on future leakage probability.

Finally, the characteristics of DMAs could be further analysed to explore the impact of variables such as ratio of ‘household’ to ‘non-household’ properties and building type (percentage of flats etc.) on water usage. Water companies keep some data on property usage, but many other variables can be found in publicly available datasets. Gaining a greater understanding of water usage based on DMA characteristics could facilitate even more accurate forecasting of flow and detection of leakage. There are additional benefits to this exploration, which could include identifying targeted strategies for demand reduction.

6 CONCLUSIONS

6.1 SUMMARY

The management of infrastructure systems must shift from a siloed approach to a system-based approach in order to address the challenges of complexity. This research develops a self-healing framework for infrastructure system management, explores how AI techniques can facilitate such an approach in infrastructure, and demonstrates how a self-healing framework can be applied to the specific case study of leakage management in a water distribution system. This study presents the key considerations needed for infrastructure system operators to implement a self-healing approach, while the case study develops AI models to deliver self-healing processes that are of particular value to water supply and distribution companies and their contractors.

6.2 CONTRIBUTIONS

6.2.1 KNOWLEDGE

The concept of self-healing systems [13] is adapted and extended for application to infrastructure systems. The first contribution to knowledge is the framework for self-healing in infrastructure systems, which allows both new and existing techniques for infrastructure management to be mapped onto a system-based approach. This presents a flexible and simple tool to consider whether an infrastructure system is managed in such a way that each process of the self-healing framework is adequately addressed and whether data is able to flow between processes. Researchers might use this framework to consider which process their research is addressing, and how their solution might be adapted to complement or enable the other elements of the framework. Infrastructure system operators could use this framework to consider whether their management and data handling processes sufficiently address the whole infrastructure system at a system level. They may also wish to map their existing management approaches onto the framework and consider factors such as modelling sophistication or levels of resilience for each process, in order to identify areas of focus for future strategy planning.

This work goes beyond the conceptualisation of a self-healing framework to consider the types of method that may enable effective implementation of the framework in infrastructure systems. AI is identified as having significant potential in the realisation of self-healing infrastructure systems, and the use of specific AI methods within infrastructure is explored from a cross-cutting perspective.

Machine learning methods are integrated into a case study that demonstrates the potential of such methods for a specific use case. By presenting the potential of AI for self-healing infrastructure systems through increasingly specific stages, and considering the cross-sectoral purposes, this research contributes a funnel through which infrastructure operators can appreciate and understand the application of AI to their own systems. Traditionally, research that applies AI to infrastructure systems is focused very much on a technical level, and the emphasis can be on understanding and applying a very specific AI method. This means that operators are presented with a case for implementing the proposed method, rather than a case for making upgrades to their system and workforce to capitalise on the many benefits that increased digitalisation can provide for a whole suite of AI tools. This study aims to make the case for the latter, by showing the potential of AI across and within infrastructure sectors, for a variety of purposes, and finally for a specific case study.

This research develops novel code which sees machine learning techniques utilised on time-series data. This code is specific to the case study in that it is designed for the purpose of leakage management processes and is set-up for the format of the case study dataset, but there are also elements of the code that are applicable to wider use cases. For example, other time-series data could be forecast or classified using the developed models. The context of alternative use cases should always be considered in order to ensure best implementation, and suitable adjustment may need to be made.

Another major contribution is the application of the self-healing framework to a case study of leakage management at the DMA level for a water distribution system in England. This case study allows specific methods for each of the self-healing processes to be investigated, with strong performance demonstrated on the large historical dataset. The framework of methods produced for this case study represents a mixed methods strategy to solve the practical problem of leakage in a water distribution system. This problem is a significant concern for water companies in the UK and the sector's economic regulator Ofwat [606].

The use of real historical data for this case study shows the need to consider data formatting and data flows at the system level, which is addressed in this study by a comprehensive pre-processing stage. The flow sensor data used in the case study represents a common and widespread type of data in water distribution system monitoring, so it is hoped that the case study is relevant to other water companies operating in the UK and other areas with district-based water management. However, differences in data management and in system setup and monitoring could mean that the leakage management framework presented in the case study would require some degree of adaptation for other areas/companies.

By considering a combination of both cutting-edge machine learning tools and more straightforward methods, the selected case study also presents a realistic approach to the upgrading of infrastructure system management, recognising that not all systems will be at a sufficient level of data maturity or have the operator skillset to implement the latest AI techniques for each process within the self-healing framework.

The case study presented in this research also makes several contributions specifically to the field of leakage management. The successful application of machine learning methods for a systems-based approach to leakage management is of value to water companies looking to improve their current leakage management strategies. Firstly, the framework demonstrates an ability to accurately forecast anomalous flow at the DMA level, rather than just the forecasting of usual (non-anomalous) flow. This offers a new anticipatory capacity to leakage management. Secondly, the detection process presents several contributions. The application of VAEs to flow data from a real water distribution system is novel, with less-widespread acoustic data provided by test-bed setups used in other studies applying AEs to leakage [554] [106]. This is significant when considering the operational feasibility of the proposed methods, because flow data is much more readily available in UK water distribution systems. That the VAE is able to capture the important characteristics of the flow data in the LVs suggests that dimensionality reduction of flow data is a valuable method for leakage detection. The use of a domain-informed loss term within the VAE loss function also represents a significant methodological contribution, and demonstrates the importance of considering application-specific factors in the development of machine learning models.

6.2.2 Policy

This research has several implications for policy. The first is making the case for improved standards for the collection, storage, management, and sharing of data within and across infrastructure systems, and between academia and industry. Availability of data underpins the ability to develop models such as those applied to the case study of leakage management in this study. The value of demonstrating proposed techniques on historical or real-time data from real-world systems is significant and only then can the necessary pre-processing be developed in order to facilitate real-world implementation of the methods.

Furthermore, the limitations placed on consumer datasets must balance the need for privacy with the potential benefits to model development. For example, access to data on customer leakage reports would have offered a more precise insight into the relationship between anomalous flow and leakage in the case study presented in this research. Mechanisms should therefore by developed to facilitate the safe sharing of relevant information between customers, operators, and researchers.

Beyond access, this study highlights the need to consider the formatting and management of data if truly systemic self-healing is to be achieved. While real-world sensor data is always likely to need some degree of pre-processing due to sensor errors and noise, the flow of data between the processes of the self-healing framework requires a consistent approach to data formatting across all operational processes. This is demonstrated in the case study presented in this study but is true for all infrastructure systems that are working towards systemic management approaches. At the operator level, this requires a standardised approach to data collection, data input, and database management, particularly when dealing with various data streams (e.g. flow data and repair data). However, at a regional or national level, this can require the standardisation of data within or even across infrastructure sectors in order to ensure that entire systems and their interdependencies can be modelled. This supports the need for initiatives such as the information management framework to support the UK's national digital twin programme [607] and the UK government's national data strategy [608].

While this section has discussed various implications related to input data policy and management, it is also essential to consider the sharing of insights generated from AI-based and systemic methods. The versatility of AI methods in infrastructure systems highlights the significant advantages of sharing insights across different sectors. Establishing expert working groups, organising industry workshops and conferences, and promoting multidisciplinary collaboration through academic journals or conferences can facilitate this knowledge exchange. Traditional research has often been confined to specific domains, hindering progress towards fully self-healing systems and the achievement of net-zero goals. By fostering knowledge and insight sharing across sectors, infrastructure operators can learn from each other's experiences and mistakes, expediting the transition to more advanced, self-healing systems and promoting sustainable practices aligned with net-zero objectives.

The findings of this work have significant policy implications for fostering digitalisation and enhancing workforce skills in the context of intelligent infrastructure systems. By highlighting the potential of AI for self-healing infrastructure systems and exploring the application of specific AI methods, this research provides a comprehensive perspective on the benefits of digitalisation. This goes beyond the technical aspects of the methods proposed to explore the value of infrastructure operators upgrading their systems and workforce to fully leverage the advantages of increased digitalisation. However, recognising that different sectors and systems are presently at different levels of maturity in digitalisation, data management, and data science capabilities, this study presents a flexible approach that allows individual processes to be substituted for more sophisticated methods when operators are at the required level. By demonstrating both advanced and simple data-driven models within a flexible self-healing framework, this research facilitates a gradual and feasible transition towards advanced AI-based methods while encouraging policymakers to prioritise investments in digital infrastructure and workforce development, recognising the transformative power of digital technologies in optimising infrastructure system management and improving overall efficiency and resilience.

Finally, the results of the case study have implications for policy from a water sector perspective. Currently, leakage detection represents the bulk of industry approaches to leakage management [606]. This study supports the need for a shift towards a whole-system approach to leakage management, demonstrating the value of a proactive element

[73]. Policy in this area should consider not only the leakage detection capabilities of water companies but also their ability to anticipate leakage and their prioritisation methods for repair scheduling.

6.3 CLOSING THOUGHTS

As our society continues to expand and urbanise, the complexity of our infrastructure systems is growing at an unprecedented pace. Urban populations are swelling, energy demands are surging, transportation networks are becoming increasingly intricate, and water systems designed a century ago are tasked with meeting the demand of millions. The traditional methods of managing these infrastructure systems are proving inadequate in handling the sheer scale and complexity of the challenges they face.

Industry is beginning to recognise the value not just of investing in innovation but in mainstreaming digital technologies to modernise infrastructure systems. The tradition 'find and fix' method of tackling problems in infrastructure is being left behind in favour of a proactive approach that puts emphasis on predicting and preventing failures before they arise [609]. During this transition to a more intelligent and autonomous approach to infrastructure systems management, it is also accepted that new solutions, if they are to be implemented for current systems, should reflect the existing operational environment in their design [610]. By bridging the gap between theoretical advancements and practical implementation within the current operational context, this work aims to contribute not only to the academic understanding of the subject but also to provide real-world tools and strategies that can drive the transformation of our infrastructure systems into adaptive, resilient, and self-healing networks, ensuring a sustainable future.

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APPENDIX A

Below is a section of code that describes some elements (number of layers, number and distribution of nodes, random seed) of hyperparameter tuning for the VAE. Not shown here is the hyperparameter tuning involved in selecting minibatch size and activation function. With the different configurations and seed values, over 1,000 versions of the model were run. The final selection was based on the IA value, SVM accuracy, and visual clarity of the latent variable distribution.

```
% This model is top be run on several computers at once, iteration values
have been individually set for each machine
for iter = 1:n


% Select no of layers between five and twelve
layers = randi([5 12]);
% Set minimum number of nodes (prior to sampling layer) between 10 and 40
Min_node = randi([10 40]);
% Set maximum number of nodes (after input layer) between 50 and 90
Max_node = randi([50 90]);
% Take difference between max and min nodes and find the step difference
in node values between layers (round to integer)
n = Max_node-Min_node;
step = round(n/(layers-3));
% Create Node value matrix
Nodes = zeros(layers,1);
% Input layer has node value equal to input size
Nodes(1) = inputsize;
% Populate Node value matrix
for tt = 1:(layers-2)
Nodes(tt+1) = Max_node - ((tt-1)*step);
end
% Note the final layer has four nodes for the sampling layer
Nodes(end) = 4;
nb = flip(Nodes);
Nodes_NN = vertcat(Nodes,2,nb);

% Build VAE nets
[E_net, D_net, Nodes] = NN_funct(layers,Nodes_NN);
nodes



% For each configuration, run 20 different random seed values
for k = 1:20
    k
    seed = randi(1000);
       . . .
% VAE and SVM code have been removed to focus on the hyperparameter
components
```

```
% For each seed and configuration, loss values, SVM accuracy, and IA
values are stored
Datatable((iter-1)*20+k,1) = array2table(seed);
Datatable((iter-1)*20+k,2) = array2table(height(Nodes_NN));
Datatable((iter-1)*20+k,3) = nodes;
Datatable((iter-1)*20+k,4) = array2table(IAmean(1,(iter-1)*20+k));
Datatable((iter-1)*20+k,5) = array2table(IAmedian(1,(iter-1)*20+k));
Datatable((iter-1)*20+k,6) = array2table(IAstd(1,(iter-1)*20+k));
Datatable((iter-1)*20+k,7) = array2table(marginSVM(1,(iter-1)*20+k));
Datatable((iter-1)*20+k,8) = array2table(accuracySVM(1,(iter-1)*20+k));
Datatable((iter-1)*20+k,9) = array2table(epochsrun(1,(iter-1)*20+k));
Datatable((iter-1)*20+k,10) = array2table(lossvec(1));
Datatable((iter-1)*20+k,11) = array2table(lossvec(2));
Datatable((iter-1)*20+k,12) = array2table(lossvec(3));

end
end
```

APPENDIX B

This research used a two-dimensional LV distribution based on the trade-off of accuracy and interpretability (through visualisation). However, higher dimensional distributions were explored in the trial phase of developing the VAE model. The results for the selected VAE configuration with a sampling layer modified for 3LVs are presented in Figure 44 below. For this case, a classification accuracy of 97.6% was achieved by the SVM (very close to the proposed 2 LVs; 98.2%). The index of agreement results are also observed to be very similar for both cases (though this is not the primary aim of this study, as the purpose is to classify the LVs rather than reconstruct the flow data). Furthermore, it is noted that interpretability of the LV space is impacted by the additional dimension. Employing more than two LVs in this context introduces intricacies that could prove challenging to explain to both users and the wider research community. Given the innovative nature of this approach, maintaining simplicity in presenting LVs is preferred to effectively showcase the method's utility and principles.

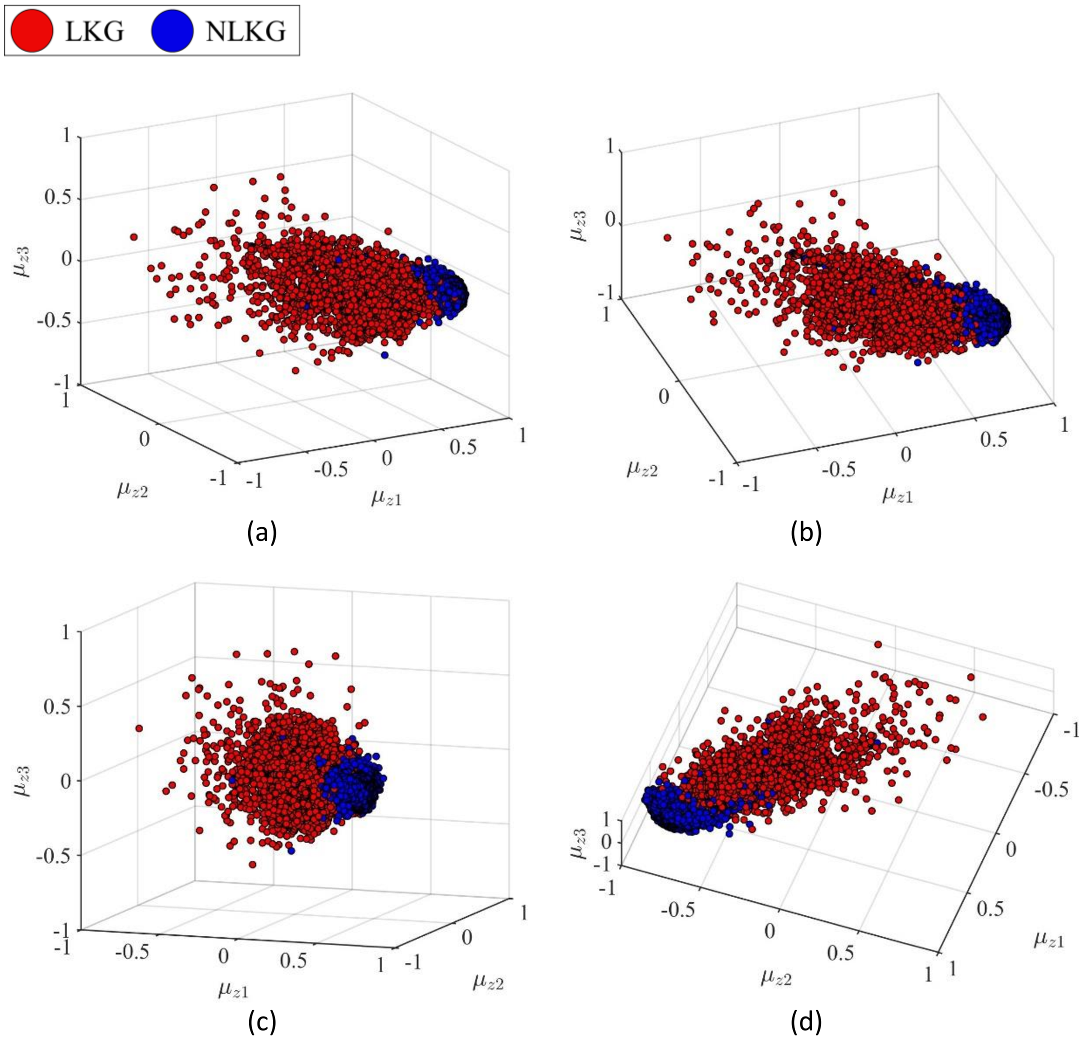

FIGURE 44: VAE RESULTS FOR 3 LVS IN 4 ANGLES