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Survey paper

A review of the use of artificial intelligence methods in infrastructure systems

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ABSTRACT

The artificial intelligence (AI) revolution 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. This paper reviews the extent to which research in economic infrastructure sectors has engaged with fields of AI, to investigate the specific AI methods chosen and the purposes to which they have been applied both within and across sectors. Machine learning is found to dominate the research in this field, with methods such as artificial neural networks, support vector machines, and random forests among the most popular. The automated reasoning technique of fuzzy logic has also seen widespread use, due to its ability to incorporate uncertainties in input variables. Across the infrastructure sectors of energy, water and wastewater, transport, and telecommunications, the main purposes to which AI has been applied are network provision, forecasting, routing, maintenance and security, and network quality management. The data-driven nature of AI offers significant flexibility, and work has been conducted across a range of network sizes and at different temporal and geographic scales. However, there remains a lack of integration of planning and policy concerns, such as stakeholder engagement and quantitative feasibility assessment, and the majority of research focuses on a specific type of infrastructure, with an absence of work beyond individual economic sectors. To enable solutions to be implemented into real-world infrastructure systems, research will need to move away from a siloed perspective and adopt a more interdisciplinary perspective that considers the increasing interconnectedness of these systems.

1. Introduction

Artificial intelligence (AI) methods enable machines to learn and infer from large volumes of data (Ertel, 2017). 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 (Luckey et al., 2021). 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 (Suganthi et al., 2015; Veres and Moussa, 2019), or a specific infrastructure sector (Abduljabbar et al., 2019). This review looks at the extent of research into the use of AI in infrastructure systems, focusing on the economic infrastructure sectors of energy, water and wastewater, transport, and telecommunications, and the intersections between sectors. As interdependent systems, there is a clear benefit to reviewing infrastructure networks as a whole, recognising areas of overlap such as the water–energy nexus, electric vehicles, and vehicular ad-hoc networks (VANETs), and common challenges, such as supply and demand forecasting, inspection, and maintenance. Not only does this review seek to ascertain which AI techniques are popularly used in infrastructure systems, but to compare the maturity and depth of research across systems, in the hope that potential research gaps can be discovered, and potential solutions informed by existing work in other fields.

2. Method

This paper adopts a systematic literature review approach in combination with a snowballing literature review method proposed by Wohlin (2014), which was applied to review papers or highly significant papers. Wohlin's systematic literature review with snowballing was chosen over a sole database search-based review due to the interdisciplinary nature of the research area, which spans a range of sec-

Abbreviations: Artificial Intelligence, AI; Adaptive neuro-fuzzy inference systems, ANFIS; Artificial neural network, ANN; Radial basis function, RBF; Recurrent neural network, RNN; Echo state network, ESN; Long short-term memory, LSTM; Multilayer perceptron, MLP; Unmanned aerial vehicle, UAV; Convolutional neural network, CNN; Support vector machine, SVM; Decision Tree, DT; Random forest, RF; Deep belief networks, DBN; Vehicular ad-hoc network, VANET; Wireless sensor network, WSN; Autonomous underwater vehicle, AUV; Gaussian mixture model, GMM; Software defined network, SDN; Quality of experience, QoE; Quality of service, QoS; Quality of transmission, QoT

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Table 1
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	

tors, making it challenging to formulate comprehensive search strings. This helped to overcome the additional difficulty of creating precise searches, with the risk of yielding many irrelevant or redundant papers (Wnuk and Garrepalli, 2018).

The systematic selection of a tentative starting set of papers was undertaken. Search terms are divided into two categories: AI terms and infrastructure terms. AI terms cover the range of subtopics within the field (Table 1). Infrastructure terms vary across systems, so these terms can be subdivided into the infrastructure systems of transportation, energy, water/wastewater and telecommunications (Table 2). These terms were used for a primary search, the results of which informed the purposes chosen for discussion later in this paper. To ensure the key papers were covered for each purpose, a range of more general terms pertaining to purpose were applied to multiple infrastructure sectors as part of a secondary search (Table 3).

The reviewed papers were categorised by AI method, infrastructure sector (or sectors), and purpose. Finally, an analysis framework, originally proposed by Sharifi for the assessment of smart city indicators (Sharifi, 2019), was selected and expanded for critical analysis of the selected papers. This enabled the literature to be evaluated against a set of criteria designed to account for various elements of planning, problem-solving, and implementation. A smart city framework was chosen as the basis of this analysis as this represents a complex system of interconnected sub-systems, spanning disciplines including engineering, governance, and politics. As infrastructure systems have both the same interconnected structure and interdisciplinary nature, a smart city perspective offers a solid foundation for analysis. Two further criteria were added to the original framework: comparison and vulnerability. The former covers the extent to which the reviewed work has compared alternative approaches, and the latter is concerned with the ability of the system to cope with failure. The inclusion of a comparison criterion was deemed necessary in order to recognise the wide range of AI models, particularly in machine learning. As linear systems, it is crucial that consideration is given to the ability of infrastructure systems to withstand failure events, justifying the addition of a vulnerability criterion.

Initial searching combined each AI term with the sector-specific infrastructure terms. An expert in telecommunication systems was consulted in order to ensure domain-specific terminology was included. Search strings combining multiple infrastructure sectors were also used, to find papers covering overlaps in infrastructure sectors such as the water–energy nexus. The results of this initial search informed the infrastructure purpose terminology selected. In an additional step, the purpose terms identified from the primary search results were then used in a secondary search, where they were combined with AI terms in order to account for key papers pertaining to specific applications. Results were subject to title screening to ensure relevance. Further exclusionary criteria were applied, which removed those not written in English, those that fell outside of the scope of infrastructure systems, or those that explored algorithms outside of machine learning models. Papers were collated, and those concerned with the same infrastructure and purpose were assessed, with factors considered including date of publication, number of citations and number of comparative models studied. Papers were also labelled to identify those that could be described as review papers. Review papers and the most relevant and comprehensive of non-review papers were then subject to snowballing. Title screening of results established relevance, and a secondary abstract screening was sufficient to apply exclusion criteria in the majority of cases. Where this was not the case, the full paper was assessed prior to inclusion. Papers were screened by a number of criteria to ensure quality. The final number of papers included in this review is 186, of which 40 are considered to be review papers.

The 186 papers included in this review were published between 1991 and 2021. 83% of papers were published in the year 2014 or later, with the publishing years of all papers shown in Fig. 1. Of the 186 selected for inclusion, 147 papers were published in journals, with the remaining being conference papers. As shown in Fig. 2, 25 journals contributed two or more papers to this review, comprising 93 papers in total.

3. Artificial intelligence fields

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 different between human and machine when interacting via a teletype system (Russell and Norvig, 2002). 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.

As the most widely adopted fields of AI in infrastructure research, machine learning and computer vision methods are reviewed below. The methods described in this section are not a comprehensive review of all techniques in machine learning and computer vision but rather the most common methods found in the body of work reviewed, as to provide context for further discussion.

3.1. 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 (Marsland, 2009). 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.

3.1.1. Learning types

Supervised Learning

In this type of learning, the system is trained using a set of examples with the desired responses provided (Li et al., 2017). Given sufficient training, which can take hours, days, or longer, the system can gener-

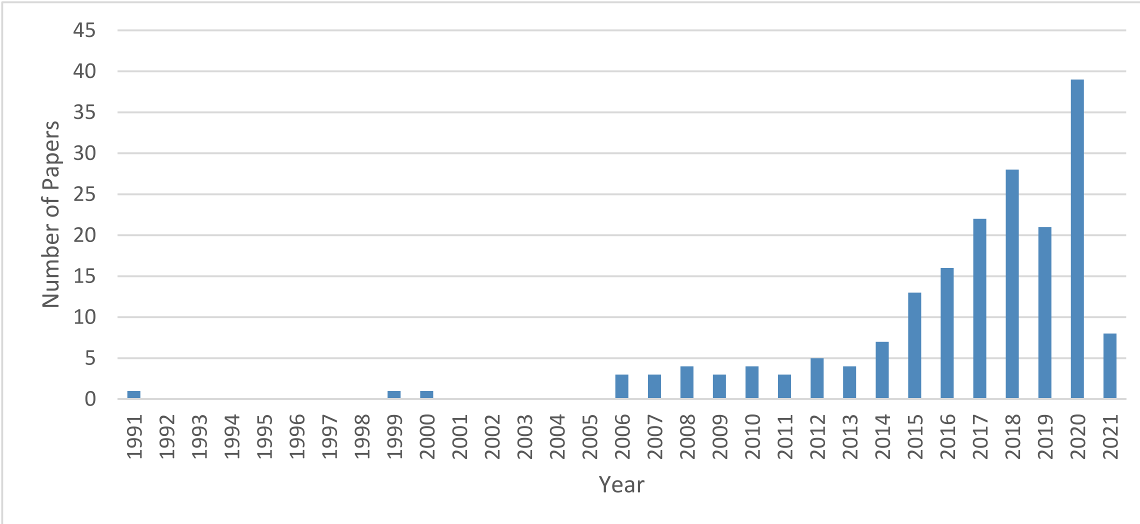

Fig. 1. Publishing years of papers included in review.

Table 2
Search terminology for different 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 3
Purpose terms used in secondary search.

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

alise in order to map inputs to outputs for new data sets. This can also be described as learning from exemplars (Marsland, 2009). Supervised learning models may require retraining to account for changes in their inputs over time.

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 (Marsland, 2009; Li et al., 2017). 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 (Fernández Maimó et al., 2018).

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 (Kubat, 2017b). 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 (Li et al., 2017). In most cases, the longer a model is run, the more refined the solution will be.

3.1.2. 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.

Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are a popular type of machine learning model that simulates 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 (Aggarwal, 2018b). 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

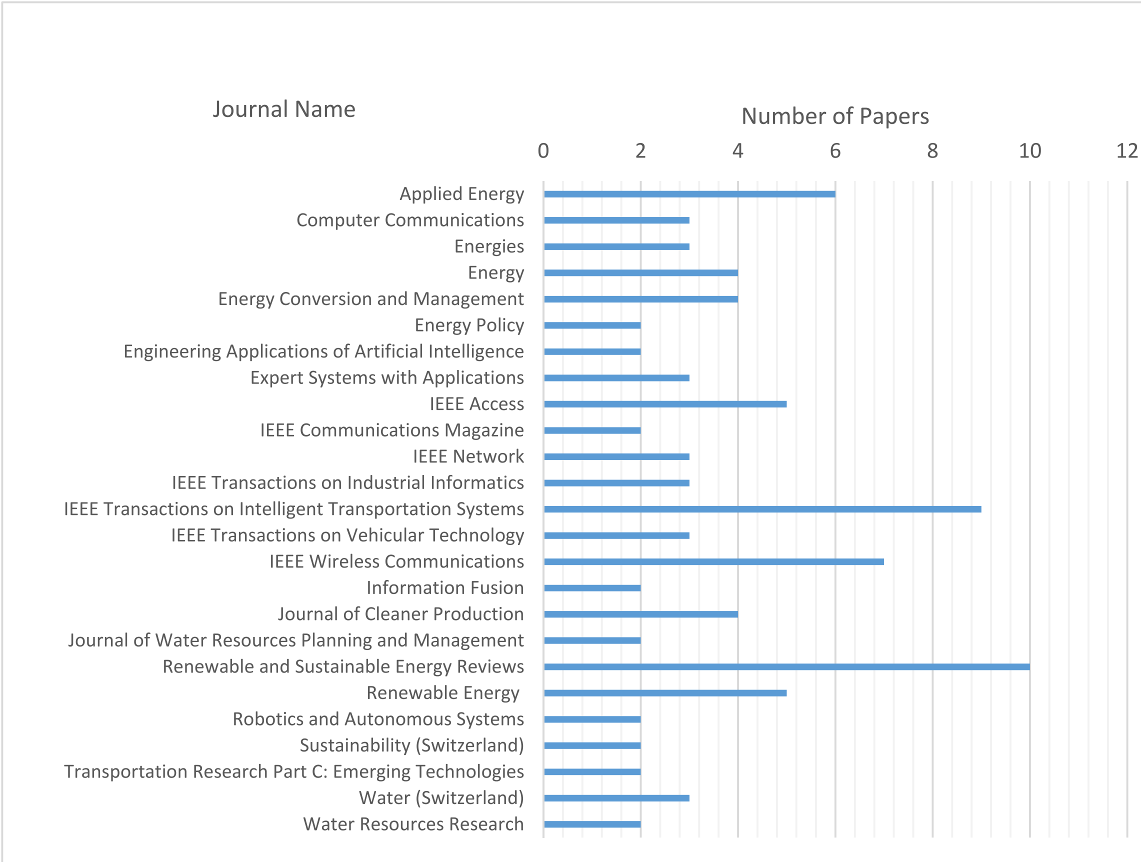

Fig. 2. Journals contributing two or more papers to this review.

into two classes based on their general architecture: feed-forward and feed-back 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 (Azadeh et al., 2008) and for pollutant removal (Fan et al., 2018) in water networks. RBF networks have also been applied to water treatment (Fan et al., 2018). 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 (Xu et al., 2019b), while LSTM networks can be found in a range of forecasting applications, where they have been used to predict energy use (Bedi and Toshniwal, 2019), telecommunication traffic (Alawe et al., 2018) and accident risk in transport networks (Ren et al., 2018), 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.

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 (Cortes and Vapnik, 1995). The SVM algorithm seeks to maximise the margin between data points and hyperplane, which it does using a loss function named hinge loss. SVM-based approaches have been used in energy demand and price forecasting (Ahmad et al., 2014; Ghoddusi et al., 2019), for routing in vehicular networks (Zhao et al., 2016), and to assess and improve quality and security in telecommunication systems (Wang et al., 2016; Mata et al., 2018; Musumeci et al., 2019).

Decision Trees (DTs) and Random Forests (RFs)

Another technique that has been applied to both classification and regression tasks is decision trees (DTs). In decision trees, 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 (Kubat, 2017a). 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 (Breiman, 2001). RFs have seen wider exploitation than DTs in infrastructure systems, where they have been applied to quality of experience (QoE) prediction (Casas et al., 2017) and anomaly detection (Gulenko et al., 2016) in telecommunication networks, price prediction (Xu et al., 2019a) and pollutant removal (Fan et al., 2018; Ye et al., 2020) in water systems, and behaviour prediction in transport (Koushik et al., 2020).

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 (Kubat, 2017c). In infrastructure, k-means has been used in telecommunication routing (Saravanan and Ganeshkumar, 2020) and for behavioural prediction in transportation modelling (Koushik et al., 2020).

3.1.3. 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 (LeCun et al., 2015). 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 (Erhan et al., 2010).

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.

3.2. Computer vision

Computer vision is concerned with learning the relationships between an 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 (Prince, 2012). Both biological and computational vision systems require several basic components: a radiation source, a camera, a sensor, a processing unit, 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 (Jahne, 2000).

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 (Mahony et al., 2020). 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 (Aggarwal, 2018b). Although developed in the 1980s, it was the development of graphics processing units, which vastly reduced run times, in the 2000s that saw CNNs take off in popularity. 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 (Aggarwal, 2018a).

4. Sectoral analysis

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.

4.1. Energy

In the energy sector, AI tools have been extensively applied to demand forecasting (Almalaq and Edwards, 2017; Bedi and Toshniwal, 2019; Robinson et al., 2017; Kalogirou, 1999; Ghanbari et al., 2013), especially at residential and building level (Mocanu et al., 2016; Ahmad et al., 2014; Wang and Srinivasan, 2017; Mat Daut et al., 2017). Further applications include price forecasting (Ghoddusi et al., 2019) and demand side management (Macedo et al., 2015). Facilitating energy use reduction is of increasing concern in this sector, and methods ranging from efficiency-centred ontologies (Tomic et al., 2010) to natural language generation of consumer advice reports (Conde-Clemente et al., 2018) 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 (Kalogirou, 2001). 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 (Shukla and Karki, 2016a,b). 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 (Suganthi et al., 2015; Li et al., 2017; Mellit and Kalogirou, 2008), and solar tracking, which often utilises computer vision tools (Carballo et al., 2019). Artificially intelligent methods of inspection and structural health monitoring for renewable energy assets have also been investigated (Bose, 2017).

4.2. Water and wastewater

AI methods have been utilised throughout water networks, from initial water treatment through to distribution and consumer-related challenges. At the supply end, much of the research has been concerned with water quality (Chau, 2006) and pollutant removal (Fan et al., 2018), in both standard and wastewater treatment (Granata et al., 2017; Ye et al., 2020; Zhao et al., 2020; Li et al., 2021). Machine learning methods have also been utilised in desalination, where they can have implications for plant design (Al Aani et al., 2019).

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 (Antunes et al., 2018; Xu et al., 2019b; Franklin, 2008; Adamowski et al., 2012) and price forecasting (Nguyen-ky et al., 2018; Xu et al., 2019a) across a range of geographic scales.

4.3. Transportation

The transportation sector has seen perhaps the most variation in tasks to which AI has been applied (Abduljabbar et al., 2019; Veres and Moussa, 2019). Looking at transportation networks as a whole, a number of knowledge representation systems, many ontology-based, have been proposed (Bouhana et al., 2015), while recent research into how the public interact with transport systems from a behavioural perspective, including transport mode selection, has benefited from a range of machine learning techniques (Koushik et al., 2020). Although it has been recognised that traffic flow and accident prediction can be utilised for a variety of urban transportation systems (Zhang et al., 2017; Doğan and Akgüngör, 2013), 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 (Jiang and Zhang, 2019; Veres and Moussa, 2019; Xie et al., 2020) and accident forecasting (Doğan and Akgüngör, 2013; Ren et al., 2018; Abduljabbar et al., 2019; Veres and

Moussa, 2019), as well as for navigational tools (Veres and Moussa, 2019). Similar tools have also been utilised in demand forecasting (Yao et al., 2018; Rodrigues et al., 2019) and destination prediction for taxi services (Veres and Moussa, 2019). Researchers have sought to apply AI to identifying and mapping road networks (Ekpenyong et al., 2009), whilst computer vision-based approaches to monitoring traffic infrastructure have been proposed (Šegvić et al., 2010). 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 (Sirohi et al., 2020). Work on the development of self-driving cars has seen massive interest in recent years, and automated reasoning (Rehder et al., 2019), machine and deep learning (Kuutti et al., 2021), and computer vision have all been utilised in what is primarily a robotics-based challenge (Abduljabbar et al., 2019; Ma et al., 2020b).

The application of AI in transport has not been limited to the roads. Though robotics, and specifically unmanned aerial vehicles (UAVs), demonstrate much potential in the monitoring of railway assets, many are still reliant on a significant level of human interaction (Flammini et al., 2016). Deep learning tools, however, have proven themselves effective at fault diagnosis in high-speed rail (Yin and Zhao, 2016), which is expected to grow in popularity as a mode of travel. While most other work in public transport has primarily focused on traffic flows or choice of transportation method (Veres and Moussa, 2019; Koushik et al., 2020), bus networks have been the subject of individual research, which focuses largely on scheduling issues (Mendes-Moreira et al., 2015).

4.4. Telecommunications

Machine learning methods are seen as highly significant for the success of the next generation of wireless networks (Li et al., 2017; Jiang et al., 2017; Kibria et al., 2018; Wang et al., 2020; Shafin et al., 2020). Research has covered a variety of network types, with some works covering the more general ‘cellular’ or ‘wireless’ networks, and others focusing specifically on software-defined networks (SDNs) (Amaral et al., 2016; He et al., 2017), optical networks (Mata et al., 2018; Musumeci et al., 2019), 5G (Li et al., 2017; Alawe et al., 2018; Le et al., 2018), and the cloud (Gulenko et al., 2016).

As in other infrastructure sectors, telecommunications has seen machine learning utilised in traffic and demand forecasting (Mastorocostas and Hilas, 2012; Mastorocostas et al., 2016; Balaguer et al., 2008; Zhang and Patras, 2018; Le et al., 2018), with recent work focused on deep learning approaches (Huang et al., 2017; Alawe et al., 2018). Another common application of machine learning, where all learning types have been employed, is in routing (Barbancho et al., 2007; Sharma et al., 2018; Mao et al., 2017, 2018; Sendra et al., 2017; Vashishth et al., 2019; Kato et al., 2017; Tang et al., 2018; Yu et al., 2018; Pei et al., 2018), 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 (Casas et al., 2017; Samadi et al., 2017; Mata et al., 2018). The design of traffic clustering techniques that factor in quality of service (QoS) has also been suggested (Wang et al., 2016). The loss of customers to rival providers is termed ‘churn’, and the accuracy of several machine learning methods in predicting this occurrence has been compared (Vafeiadis et al., 2015).

Security is a critical concern in telecommunications, especially in wireless and SDNs (Lv et al., 2021). A spectrum of machine learning approaches have been used in anomaly detection (Mata et al., 2018; Musumeci et al., 2019; Gulenko et al., 2016; Fernández Maimó et al., 2018), identifying denial-of-service (Meti et al., 2017; Polat et al., 2020; Hussain et al., 2021; Ahuja et al., 2021) and intrusion attacks (Song et al., 2017; Abubakar and Pranggono, 2017; Tang et al., 2016), and selecting an appropriate response (Ashraf and Latif, 2014).

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 (Zhang et al., 2018).

4.5. 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 (Zaidi et al., 2018). Hydropower, the generation of electricity by 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 (Grubert, 2016), while the supervised technique of SVM has been used to analyse the division between hydropower and irrigation in worldwide reservoir usage trends (Zeng et al., 2017).

On a consumer level, there are many systems that both utilise water and require energy, such as dishwashers, washing machines, and showers. Research has used SVMs to classify such water end-use events on a residential scale (Vitter and Webber, 2018).

4.6. Energy and transport

Energy demand forecasting for transportation has received less attention than equivalent forecasting for buildings, although researchers have recognised 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 (Geem, 2011; Al-Ghandoor et al., 2012; Murat and Ceylan, 2006; Pamuła and Pamuła, 2020).

AI tools have 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 (Qi et al., 2017), while research at network level has focused on routing, charging point selection, and integration of electric vehicles into the smart grid (Rigas et al., 2015), all of which can benefit from some level of local demand forecasting (Saputra et al., 2019; Lan et al., 2021). At the vehicle-grid intersection, minimising energy peaks can be done through load balancing, congestion pricing, and market selling and purchasing strategies.

4.7. 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 (Buyukyildiz et al., 2014).

4.8. Energy and telecommunications

Recent work in telecommunications has begun 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 (AlQerm and Shihada, 2017), and research on utilising UAVs to provide dynamic networks has prioritised low energy usage (Zhang et al., 2018).

4.9. 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 (Lai et al., 2015; Zhao et al., 2016; Tang et al., 2019; Saravanan and Ganeshkumar, 2020) and security (Zhang and Zhu, 2018; So et al., 2018). AI tools have also been used to improve VANET efficiency in the context of enhanced road safety, with k-means clustering utilised to improve safety at congestion points such as intersections (Taherkhani and Pierre, 2016).

4.10. 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 (Mitra et al., 2016) and communicate warnings for those at risk (Bande and Shete, 2017). There remains an absence of work utilising AI to predict, assess, or mitigate the effects of flooding on telecommunications infrastructure.

5. 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.

5.1. System provision

AI tools have been 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.

5.1.1. Site selection

In the oil and gas sector, comprehensive review papers have discussed the potential of robotics in exploration and site selection (Shukla and Karki, 2016a,b). Research regarding applications has, to date, been limited to establishing the capabilities of UAVs (Tisdale et al., 2009) and autonomous underwater vehicle (AUVs) (Hiller et al., 2012), 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 to be used by the energy industry in the site selection process. The use of fuzzy logic in renewable energy systems has been reviewed (Suganthi et al., 2015), with the authors finding that this form of automated reasoning has been widely used to assess the suitability of potential solar (Charabi and Gastli, 2011, 2013; Gunderson et al., 2015; Wu et al., 2014), wind (Machias and Skikos, 1991; Aydin et al., 2010; Yeh and Huang, 2014; Azadeh et al., 2014), biomass (Ayoub et al., 2007; Yılmaz Balaman and Selim, 2014), and hybrid renewable energy (Aydin et al., 2013) 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 (Yılmaz Balaman and Selim, 2014).

Fuzzy logic has also been employed for site selection of transportation infrastructure, albeit to a much lesser extent. For example, an integrated fuzzy logic and multicriteria decision model approach has been employed to identify potential sites for car parking infrastructure (Farzanmanesh et al., 2010; Sasan et al., 2018) and for electric vehicle charging stations (Guo and Zhao, 2015). 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.

5.1.2. Dynamic network creation

In the field of telecommunications, recent work has proposed the use of 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.

Machine learning approaches have been explored to facilitate effective network provision through UAVs. In one example, a machine learning framework based on a Gaussian mixture model (GMM) has been utilised to predict network congestion for the purpose of deploying UAVs in a way that minimises power usage for mobility and transmission (Zhang et al., 2018).

5.2. Forecasting

5.2.1. Supply

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, regression, time series, RFs, deep learning, and hybrid models have all been used to predict meteorological variables and associated power outputs in renewable systems (Suganthi et al., 2015; Zaidi et al., 2018; Zahraee et al., 2016; Lin et al., 2020; Alizamir et al., 2020). Solar radiation, wind speed, and rainfall forecasting allow researchers to assess the energy generation potential of current and prospective solar, wind, and hydropower energy sites (Zaidi et al., 2018; Zhen et al., 2020; Ahmad and Chen, 2020). 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 (Tan et al., 2012). Outside of renewables, an ANN-based approach outperformed traditional methods in forecasting oil, gas, and water production rates for a hydrocarbon reservoir (Negash and Yaw, 2020).

5.2.2. Demand

AI methods, dominated by machine learning, have been incredibly widely used in demand forecasting for infrastructure systems. Table 4 summarises the machine learning techniques applied to demand forecasting in each paper reviewed.

Numerous papers and several review papers have examined the use of machine learning in energy demand forecasting. The majority of work to date has taken a supervised learning approach, likely due to the large amounts of available historic data, with ANNs and SVMs the most common methods (Kalogirou, 1999; Raza and Khosravi, 2015; Wang and Srinivasan, 2017; Ahmad et al., 2014; Mat Daut et al., 2017; Ghoddusi et al., 2019; Geem, 2011; Khwaja et al., 2020; Ahmad and Chen, 2020). Recent work has explored deep learning for energy forecasting (Bedi and Toshniwal, 2019; Almalaq and Edwards, 2017; Hafeez et al., 2020; Yang et al., 2020), with evidence suggesting it outperforms standard machine learning methods (Mocanu et al., 2016). Forecasting has been attempted across a range of temporal and geographical scales, from 30 min ahead to annual projections (Azadeh et al., 2008) and from household to regional levels (Bui et al., 2020; Johannesen et al., 2019; Robinson et al., 2017; Pham et al., 2020). Limited work has also looked at forecasting transportation energy demand (Geem, 2011; Murat and Ceylan, 2006; Al-Ghandoor et al., 2012; Pamuła and Pamuła, 2020).

Many of these machine learning techniques have also been applied to water demand forecasting, with ANNs again dominating among chosen methods (Franklin, 2008; Zaidi et al., 2018). Comparative studies have shown ANN-based approaches capable of achieving greater accuracy in water demand prediction than other machine learning systems (Adamowski et al., 2012; Antunes et al., 2018). A recent paper has sought to apply deep learning to this task, which yielded promising results in hourly urban water demand forecasting (Xu et al., 2019b).

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 (Mastorocostas and Hilas, 2012; Mastorocostas et al., 2016), while ANNs have been utilised to predict incoming requests in call centres (Balaguer et al., 2008) and to forecast traffic in telecommunications networks (Zhang and Patras, 2018). Gaussian process regression and online Bayesian moment matching are other approaches which have been applied to online flow prediction, for the purpose of efficiently routing large traffic flows (Poupart et al., 2016). Much of the recent work in the field of telecommunications has focused on the application of machine learning to forecasting in 5G networks (Le et al., 2018), with deep learning increasingly common in this field (Huang et al., 2017; Alawe et al., 2018). Customer churn describes the movement of consumers away from a given supplier, and there has been significant utilisation of machine learning for churn forecasting in the telecommunications industry. An SVM-based approach has shown the highest accuracy of common machine learning methods (Vafeiadis et al., 2015).

The transportation sector has seen machine learning applied to traffic, destination, and mode choice forecasting (Veres and Moussa, 2019), each a factor in anticipating network demand. ANNs have been used to predict traffic flows in road networks (Ma et al., 2020a) and combined with deep learning to predict citywide car, taxi, and public bike share traffic flows (Abduljabbar et al., 2019; Yao et al., 2018; Jiang and Zhang, 2019; Zhang et al., 2017; Gu et al., 2020; Xu et al., 2020; Cui et al., 2020; Chen et al., 2021; Du et al., 2020; Xie et al., 2020). In addition, a deep learning approach that uses ANNs to combine textual and time-series data has attempted to forecast taxi demand in areas with large-capacity public events by incorporating contextual explanations for taxi use (Rodrigues et al., 2019). Taxi systems have also been the subject of work on destination prediction, where ANNs, in the form of MLPs and CNNs, have proven effective for multi-scale trajectory and destination forecasting (Lv et al., 2018). In aviation, an LSTM-based model was able to predict air traffic well despite anomalies in traffic control (Gui et al., 2020). 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 has been used to gain an understanding of the factors influencing individuals' transport choices. A range of machine learning tools have been applied to this problem, but comparative studies find an RF classifier gives the greatest accuracy (Koushik et al., 2020; Jahangiri and Rakha, 2015). Results have found journey length to be the most important variable in transport mode selection, although climate was also found to contribute significantly (Hagenauer and Helbich, 2017).

5.2.3. Price

Although an extensive range of machine learning methods have been used in energy price prediction (Lu et al., 2019; Jahangir et al., 2020), a thorough review has found ANNs, SVMs and genetic algorithms (GAs) to be the most popular (Ghoddusi et al., 2019). While the forecasting of crude oil and electricity prices dominates the work in this field, it was found that a handful of papers predict the prices of other energy commodities such as fuelwood, natural gas, and carbon prices using machine learning (Lu et al., 2020). Deep learning has only seen widespread use in the projection of electricity prices, remaining relatively unexplored in the crude oil equivalent.

ANNs (Nguyen-ky et al., 2018) and RF regressor models (Xu et al., 2019a) 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.

5.2.4. Safety

In the transportation sector, machine learning methods have also been applied to the forecasting of road accidents and casualties (Abduljabbar et al., 2019), as well as the severity of incidents (Veres and Moussa, 2019). ANNs have proven the most effective of the methods trialled, with one example exploring how railway development policy would impact highway casualties (Doğan and Akgüngör, 2013). Further work has used an LSTM-based deep learning model for predicting traffic accident risk based on data from Beijing, China (Ren et al., 2018).

5.3. Routing

The machine learning methods used for routing in the reviewed papers have been summarised in Table 5.

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 (Wang et al., 2018; Mao et al., 2017; Zorzi et al., 2015). Optimal routing processes minimise delays and improve QoS. In WSNs, a routing protocol using an unsupervised ANN in the form of a self-organising map (SOM) has performed favourably when compared to existing routing methods, especially in scenarios with high levels of node failure (Barbancho et al., 2007). In opportunistic networks, where link performance is subject to high variability, ANNs and DTs have been successfully applied to routing (Sharma et al., 2018), although more recent work has claimed a GMM approach outperforms existing machine learning tools (Vashishth et al., 2019). Deep learning has also been applied to routing in both wired and wireless networks, where several supervised and reinforcement learning methods have been shown to reduce delays and improve throughput (Kato et al., 2017; Tang et al., 2018).

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 has been the favoured tool in recent work on routing in SDNs (Sendra et al., 2017), often in combination with deep learning architecture (Mao et al., 2018; Yu et al., 2018). An alternative supervised deep learning approach has been applied to SDN routing in order to minimise end-to-end delay in virtual network function selection (Pei et al., 2018).

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 infrastructure 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, including supervised ANN and SVM methods (Tang et al., 2019; Zhao et al., 2016), an unsupervised K-means approach (Lai et al., 2015), and deep reinforcement learning (Saravanan and Ganeshkumar, 2020).

Machine learning has also been applied to the routing of vehicles in transportation networks. For urban road traffic routing, GPS data has been used in combination with an end-to-end deep learning approach to attempt to apply the knowledge of experienced drivers when determining route selection (Veres and Moussa, 2019; Li et al., 2019).

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. To date, most of the work in this field is at agent, rather than system, level (Yang et al., 2019; Ma et al., 2020b). Deep learning, and deep reinforcement learning in particular, has been effectively applied to lateral and longitudinal control systems in autonomous vehicles, where the self-optimising nature of such techniques makes them well suited to dynamic road environments (Kuutti et al., 2021). In the shipping sector, fuzzy logic can support dynamic decision making for autonomous navigation through international shipping routes (Wu et al., 2020).

5.4. 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.

Table 4
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
Geem (2011)	*E/T*	○								
Khwaja et al. (2020)	*E*	●			○					
Ghanbari et al. (2013)	*E*	○							○ ANN + FL	● Genetic algorithm
Bedi and Toshniwal (2019)	*E*	○	○					●		
Hafeez et al. (2020)	*E*	○						●		
Yang et al. (2020)	*E*		○	○	○			●		
Mocanu et al. (2016)	*E*	○	○					●		
Azadeh et al. (2008)	*E*	○								
Bui et al. (2020)	*E*	○	○		○				● ANN + firefly algorithm	
Johannesen et al. (2019)	*E*				●	○				
Robinson et al. (2017)	*E*	○	○	●	○	○				
Pham et al. (2020)	*E*			○	●					
Murat and Ceylan (2006)	*E/T*	○								
Al-Ghandoor et al. (2012)	*E/T*								○ ANN + FL	
Pamuła and Pamuła (2020)	*E/T*							●		
Franklin (2008)	*W*	○								
Adamowski et al. (2012)	*W*	○								
Antunes et al. (2018)	*W*	○	○		○	●				
Xu et al. (2019b)	*W*	○	○					●		
Mastorocostas and Hilas (2012)	*C*								○ ANN + FL	
Mastorocostas et al. (2016)	*C*								○ ANN + FL	
Balaguer et al. (2008)	*C*	○								
Zhao et al. (2004)	*C*	○								
Zhang and Patras (2018)	*C*	○	○					●		
Poupart et al. (2016)	*C*	○								● Gaussian Process
Le et al. (2018)	*C*	○					○			○ Gaussian process
Huang et al. (2017)	*C*							●		
Alawe et al. (2018)	*C*							●		
Vafeiadis et al. (2015)	*C*	○	●	○						○ Naïve Bayes
Ma et al. (2020a)	*T*	○	○						● ANN + ARIMA	
Yao et al. (2018)	*T*	○		○				●		
Jiang and Zhang (2019)	*T*							○		
Zhang et al. (2017)	*T*	○						●		
Gu et al. (2020)	*T*	○						○	● DL + Bayesian	
Xu et al. (2020)	*T*	○				○		●		○ Bayesian Gaussian tensor decomposition
Cui et al. (2020)	*T*	○	○					●		
Chen et al. (2021)	*T*							○		
Du et al. (2020)	*T*		○					○	● CNN + gated recurrent units	
Rodrigues et al. (2019)	*T*		○					●		○ Gaussian Process
Lv et al. (2018)	*T*	○						●		
Gui et al. (2020)	*T*		○					●		
Jahangiri and Rakha (2015)	*T*		●	○	●	○				
Hagenauer and Helbich (2017)	*T*	○	○	○	●					○ Naïve Bayes

5.4.1. *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, 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 (Shukla and Karki, 2016a,b), but utilising their full potential requires a greater level of autonomy. Other AI methods can aid robots undertaking inspections. For example, machine-learning-based computer vision can be integrated into UAVs to identify, map out and monitor electrical infrastructure. However, while computer vision has been applied to vegetation detection in electrical infrastructure, it is potential to detect defects in cables or insulation remains undeveloped (Mirallès et al., 2014).

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 structures and a deep learning approach to dealing with anomalies in sensor data (Bao et al., 2019). RFs and DT algorithms have shown high effectiveness in predicting anomalies in wind turbine function, informing preventative maintenance strategies (Hsu et al., 2020). Utilising both machine learning and automated reasoning, an 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 (Bose, 2017).

An interesting use of computer-based monitoring has been employed to identify abnormalities in a water distribution network. An

Table 5
Machine learning methods used in papers on routing. Only papers which proposed their own techniques were 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. T and C correspond to transport and telecommunications respectively.

Reference	Sector	Machine learning method							
		ANN	SVM	DT	RF	K nearest neighbour	K-means	DL	Other
Mao et al. (2017)	*C*							○	
Zorzi et al. (2015)	*C*							○	
Barbancho et al. (2007)	*C*	○							
Sharma et al. (2018)	*C*	●		○					
Vashishth et al. (2019)	*C*	○		○		○			● GMM
Kato et al. (2017)	*C*							○	
Tang et al. (2018)	*C*							○	
Sendra et al. (2017)	*C*	○							
Mao et al. (2018)	*C*							○	
Yu et al. (2018)	*C*							○	
Pei et al. (2018)	*C*							○	
Tang et al. (2019)	*C/T*	○							
Zhao et al. (2016)	*C/T*		○						
Lai et al. (2015)	*C/T*						○		
Saravanan and Ganeshkumar (2020)	*C/T*		○					●	○ Q-learning
Li et al. (2019)	*T*							○	
Rehder et al. (2019)	*T*	○							● Bayesian network
Yu et al. (2021)	*T*		○					●	
Wu et al. (2020)	*T*								○ Fuzzy logic

ANN has been trained using a continually updated historic database to build a probability density model for future flow profile, while a fuzzy inference system compares latest observed flow values with predicted flows. Major discrepancies generate an alert, which was found to correspond with confirmed pipe bursts in 44% of trial cases (Mounce et al., 2010). In water systems dependent on a network of sensors, such as those used to determine water quality indicators in wastewater systems, faulty sensors are not uncommon, and can cause significant data quality issues. An LSTM deep learning technique has used for automatic fault detection in wastewater sensors, correctly identifying faults in over 92% of cases (Mamandipoor et al., 2020).

AI has been utilised for safety monitoring in transport networks, where a computer vision-based approach has been explored for traffic infrastructure inventory creation and assessment (Zhang and Zhu, 2018). 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 (Zhang et al., 2020). Deep learning has been applied to fault detection for high speed rail, where a DBN consisting of stacked restricted Boltzmann machines outperforms ANN and k nearest neighbour methods in automated fault diagnosis (Yin and Zhao, 2016). 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.

5.4.2. 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. The machine learning methods applied to this purpose in the reviewed papers have been summarised in Table 6.

In telecommunications, network security is a major consideration and has been the subject of a large volume of research in recent years (Lv et al., 2021). 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 (Song et al., 2017; Abubakar and Pranggono, 2017; Meti et al., 2017; Nanda et al., 2016; Polat et al., 2020). Deep learning tools have also been employed for security purposes in SDNs. For example, a supervised deep neural network approach has been used in intrusion detection (Tang et al., 2016), and various deep learning techniques have been shown to be highly accurate for multi-vector denial-of-service attack detection (Hussain et al., 2021; Ahuja et al., 2021).

The use of machine learning in optical networks has been 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 (Mata et al., 2018; Musumeci et al., 2019).

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, Bayesian methods and an SVM-based approach (Gulenko et al., 2016). Ten-fold cross-validation was undertaken, which found that all algorithms were able to predict anomalies with relatively high precision and recall measures, although this can be diminished when aging effects are considered. 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 (Fernández Maimó et al., 2018). This two-layer approach has demonstrated an ability to self-adapt in real-time, based on the volume of network flows.

5.5. Quality

5.5.1. Water quality

AI has been used to assess and improve water quality at various stages of the water treatment cycle (Chau, 2006). 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 (Chen et al., 2020a). Looking at other machine learning methods, support vector regression has proven more effective than a regression tree approach to predicting key wastewater quality indicators across

Table 6
Machine learning methods used in papers on security and hazard detection. Only papers which proposed their own techniques were 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. T and C correspond to transport and telecommunications respectively.

Reference	Sector	Machine learning method								
		ANN	SVM	DT	RF	K-means	Naïve Bayes	DL	Hybrid	Other
Lv et al. (2021)	*C*							○		
Song et al. (2017)	*C*			○	○					
Abubakar and Pranggono (2017)	*C*	○								
Meti et al. (2017)	*C*	○	●				○			
Nanda et al. (2016)	*C*			○			○			● Bayesian network
Polat et al. (2020)	*C*	○	○				○			● K nearest neighbour
Tang et al. (2016)	*C*	○	○	○	○		○	●		
Hussain et al. (2021)	*C*							○		
Ahuja et al. (2021)	*C*		○					●		
Gulenko et al. (2016)	*C*		○	○	○		○			
Fernández Maimó et al. (2018)	*C*							○		

a range of drainage basins, though both were found to give robust predictions (Granata et al., 2017). The value of fuzzy logic in quality assessment has also been established, primarily in fresh water systems (Chau, 2006). Finally, a hybrid approach combining DTs and a shallow CNN has been effective in analysing the pollutant levels of industrial wastewater (Chen et al., 2020b).

Once water has entered a treatment facility, it is critical that operators know 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 (Zhao et al., 2020; Al Aani et al., 2019). While ANN-based methods dominate, techniques such as SVMs, RF, ANFIS, and deep learning have also been successfully utilised, and hybrid methods that combine ANNs with other machine learning approaches have shown high accuracy and robustness (Fan et al., 2018; Bhagat et al., 2020).

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. This can assist with treatment plant design. ANNs have shown high levels of accuracy when predicting membrane efficiency under a range of operating conditions, showing the greatest superiority over classical methods at high concentration levels. ANNs have also been utilised to identify factors affecting fouling, which is the process of particle deposition on or in a membrane, leading to performance degradation (Al Aani et al., 2019; Li et al., 2021).

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 (Ye et al., 2020).

ANN-based models have 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 (Al Aani et al., 2019).

5.5.2. Quality of service

For telecommunication companies, providing a high QoS is critical for preventing customer churn. AI has been applied in the assessment of consumer QoE, as well as to improve network quality in a variety of ways.

Supervised machine learning has been applied to QoE assessment for smartphone users in cellular networks. Key performance indicators incorporated user-reported data on experience and accessibility with QoS traffic measurements, to quickly and accurately predict end-user satisfaction. A range of classifiers were considered, with RF and DT-based models outperforming SVM, ANN, and Naïve Bayes approaches (Casas et al., 2017). A QoS-centred approach to classification of traffic flows in SDNs has been proposed, with an SVM-based classifier assigning QoS classes to traffic flows through a semi-supervised machine learning approach. Key factors such as delay, jitter, and loss rate were used to assign a QoS class, which the authors suggest using to efficiently re-route elephant flows (Wang et al., 2016). To predict quality of transmission (QoT) in optical networks, case-based reasoning, SVM, and RF methods are among the machine learning methods that have been utilised (Mata et al., 2018). An ANN approach has achieved high levels of accuracy with microsecond response time, facilitating dynamic network operation (Samadi et al., 2017)

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 has been proposed for an unsupervised machine learning approach to selecting fog nodes in a 5G network, with the aim of reducing system latency (Balevi and Gitlin, 2017).

6. Discussion

This section reflects on the review findings and evaluates these using an existing analysis framework developed from a review of smart city assessment papers and their indicators.

6.1. Review papers

Of the 186 papers in this review, 40 were considered to be review papers as they survey or give an overview of existing research on AI in an area of infrastructure. While most are concerned with the present state of the art, some look ahead to predict future challenges and opportunities in their field (Jiang et al., 2017) . Many of the review papers deal with a particular subsector rather than a full sector of infrastructure. For example, reviews have been undertaken pertaining specifically to solar energy within the energy sector (Mellit and Kalogirou, 2008) and optical networks within telecommunications (Mata et al., 2018; Musumeci et al., 2019). It is also noted that some review the use of AI only for a specific purpose, such as forecasting (Raza and Khosravi, 2015; Almalaq and Edwards, 2017). Nonetheless, the existence of a body of work that seeks to surmise the progress of AI in the field of infrastructure indicates the extent of development in this area. The distribution of review papers also highlights the sectors, purposes, and subcategories of AI that have been the subject of the greatest degree of research, and those areas that lack significant study. Fig. 3 shows the review papers that focus on the field of machine learning, as well as various subcategories of machine learning. This

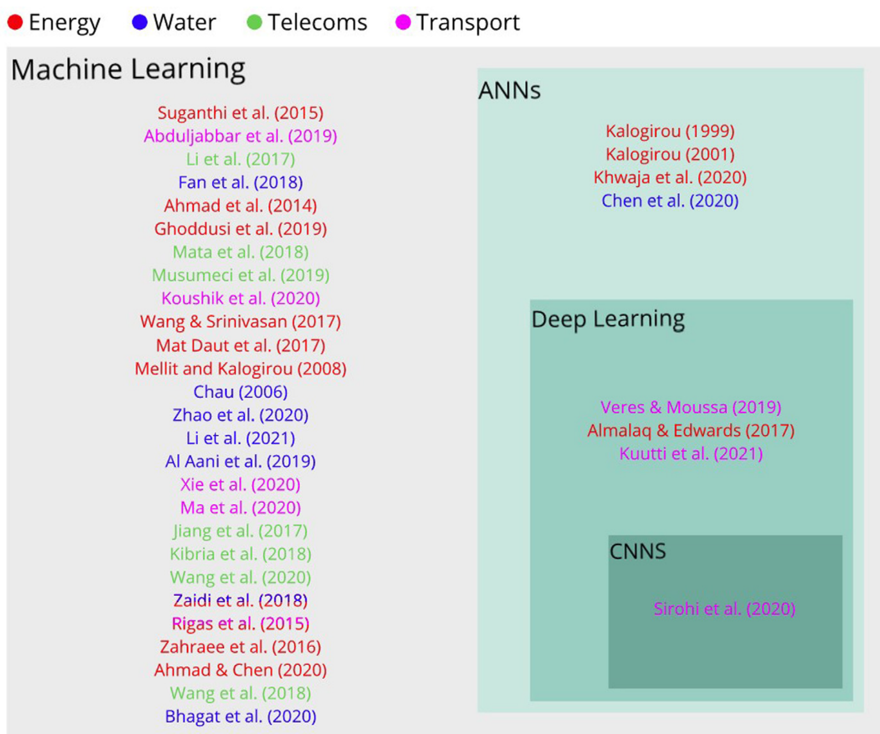

Fig. 3. References of review papers covering fields of machine learning.

represents a significant majority of review papers, with those absent from this selection focusing instead on robotics (Shukla and Karki, 2016a,b; Yang et al., 2019), or computer vision (outside of CNNs) (Mirallès et al., 2014). The infrastructure sector with the most existing review papers is energy, followed by telecommunications. Only two papers were identified as sitting at the overlap between sectors, which were concerned with energy and water, and energy and transport.

6.2. Characteristics of machine learning methods

With numerous machine learning tools available, and further sub-types of each, the justification for selecting one method over another is not always immediately evident. Table 7 presents 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.

6.3. Analysis

The structure of this analysis is based on a framework proposed by Sharifi, which consists of 11 qualities with associated evaluation criteria (Sharifi, 2019). 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 (Szpilko, 2020). Two additional criteria, comparison and vulnerability, have been added to the original framework in order to align the analysis with AI in infrastructure. Table 8 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 paper. Criteria with limited coverage would benefit from greater consideration in future research in this field; this is explored more in a later section on further work. 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.

6.3.1. 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, applied a total of 28 evaluation criteria across six dimensions: safety and quality, economy and benefit, social impression, environment and ecology, regulation, and policy (Yeh and Huang, 2014). Another example is the site selection of electric vehicle charging stations, which also made use of fuzzy logic and considered 11 sub-criteria within economic, social, and environmental sectors (Guo and Zhao, 2015).

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 the 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 (Geem, 2011; Al-Ghandoor et al., 2012; Murat and Ceylan, 2006).

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 (Tang et al., 2019), other work has incorporated 12 inputs, including buffer occupancy and success ratio (Sharma et al., 2018), and sought to account for multiple noise parameters (Barbancho et al., 2007).

6.3.2. 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 QoE in

Table 7
Characteristics of machine learning techniques.

Method	Strengths	Weaknesses	Example of effective use
ANN	ANNs are a versatile approach to solving complex, non-linear problems (Aggarwal, 2018c). 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 (Mat Daut et al., 2017).	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 re-training over time (Mat Daut et al., 2017). ANNs can suffer from overfitting and local minima issues (Ghoddusi et al., 2019).	ANNs have been applied to short-term energy load forecasting, where they have outperformed traditional methods due to the highly nonlinear characteristics of short-term prediction. Able to approximate functions regardless of non-linearity and without prior knowledge of functional form, ANNs also perform consistently across variation in time intervals (Raza and Khosravi, 2015).
Deep learning	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 (LeCun et al., 2015).	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 (Aggarwal, 2018d). 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.	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 (Mao et al., 2017).
SVM	While both ANN and SVM can solve the nonlinear problems, SVM only requires a small quantity of data to do so Mat Daut et al. (2017). SVM methods are able to effectively handle data with both high degrees of uncertainty and heterogeneity. SVM classifiers typically run at good speeds (Ghoddusi et al., 2019).	SVM is a black box approach, so the intrinsic relations between inputs and outputs cannot be completely known. SVM has limited tolerance for noisy data or data with missing values, and can be susceptible to overfitting (Ghoddusi et al., 2019).	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 (Mat Daut et al., 2017). 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 (Hong, 2009).
RF	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 (Ye et al., 2020). RFs do not suffer from overfitting, and are the fastest tree-based technique (Ghoddusi et al., 2019).	RF is another black box approach. RF's execution time, though typically low, can significantly increase with large volumes of data (Song et al., 2017). RFs for large datasets can also take up large amounts of memory.	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 (Hagenauer and Helbich, 2017).
K-means	K-means is a scalable, rapid, and simple learning algorithm, able to handle large quantities of data (Taherkhani and Pierre, 2016).	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 (Kubat, 2017c).	K-means clustering has been effectively applied to data congestion control in 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 (Taherkhani and Pierre, 2016).

telecommunication end-users combined a passive monitoring tool with a feedback application in participants' smartphones. In total, around 700 instances of feedback were recorded, which helped to establish relationships between QoE and several other performance indicators, such as length of session (Casas et al., 2017). 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 (Yeh and Huang, 2014).

6.3.3. Context-sensitivity

Many techniques explored in this paper have been applied to particular contexts, as the complex nature of tools such as machine learning often makes then unsuitable to broad circumstances. Several papers have chosen to frame their findings in a context-specific way through the use of case studies (Azadeh et al., 2014; Aydin et al., 2013; Xu et al., 2019a; Zhang et al., 2017), 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 case, time-series data was combined with textual data for taxi demand prediction in event areas. The authors utilise online information regarding event scheduling at venues within the study area, recognising that this is likely to influence local taxi demand (Rodrigues et al., 2019).

6.3.4. 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 at a local level, while strategic plans often take a broader approach and deal with significant geographic areas and/or

Table 8
Analysis framework (Zhang and Zhu, 2018; Yeh and Huang, 2014; Casas et al., 2017; Lv et al., 2021; Rodrigues et al., 2019; Alawe et al., 2018; Doğan and Akgüngör, 2013; Ekpenyong et al., 2009; Lu et al., 2019; Guo and Zhao, 2015; Zaidi et al., 2018; Antunes et al., 2018; Mocanu et al., 2016; Wu et al., 2020; Samadi et al., 2017; Aydin et al., 2013; Balevi and Gitlin, 2017; Gu et al., 2020; Ye et al., 2020; Vashishth et al., 2019; Meti et al., 2017; Yin and Zhao, 2016).

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 (Zhang and Zhu, 2018)	Multi-criteria, multi-dimension (Yeh and Huang, 2014)
Stakeholder engagement	Whether participatory approaches (which include interviews, questionnaire surveys, focus group discussions, community workshops, and consultations) have been considered in the development and implementation of the selected tools.		Includes opinion as an indicator (Yeh and Huang, 2014)	Large numbers of feedback (Casas et al., 2017)
Context-sensitivity	Whether the selected tools take account of user needs and context-specific needs and challenges.		Overview of method with examples (Lv et al., 2021)	Method adapted to context (Rodrigues et al., 2019)
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 (Alawe et al., 2018)	Looks at effects of policy (Doğan and Akgüngör, 2013)
Uncertainty management	Whether iterative processes have been adapted and future scenarios have been developed to take account of future uncertainties.		Automatic updates considered (Ekpenyong et al., 2009)	Adaptive technique (Lu et al., 2019)
Interlinkages and interoperability	Whether interlinkages and interoperability between different indicators and systems have been considered in the assessment process.		Research at an area of overlap between systems (Guo and Zhao, 2015)	Nexus between infrastructures (Zaidi et al., 2018)
Temporal changes	Whether selected tools track temporal changes.		Short-term forecasting (Antunes et al., 2018)	Range of temporal scales and resolutions (Mocanu et al., 2016)
Flexibility	Whether issues related to flexibility, scalability, and replicability have been considered by the selected tools.		Method specific to application (Wu et al., 2020)	Scalable and adjustable method (Samadi et al., 2017)
Feasibility	Whether issues related to technical and financial feasibility have been considered by the selected tools.		No examples found	Multiple indicators to consider feasibility (Aydin et al., 2013)
Presentation and communication	Whether the selected tools have taken appropriate approaches to effective presentation and communication of the results.		Short, clearly presented paper (Balevi and Gitlin, 2017)	Good visualisations (Gu et al., 2020)
Comparison	Whether selected tools are compared against other methods, using a common dataset that is large enough to be representative.		Two models compared (Ye et al., 2020)	Several independent models compared (Vashishth et al., 2019)
Vulnerability	Whether potential failure methods have been considered by the selected tools.		Improving network security (Meti et al., 2017)	Focus on failure identification (Yin and Zhao, 2016)
Action-oriented approach	Whether assessment findings have been used for developing action plans and broader infrastructure implementation roadmaps.		No examples found	No examples found

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 was make to predict the impact of railway development policy on road casualties in Turkey (Doğan and Akgüngör, 2013). Though not aligned with any stated strategic goal, a substantial body of recent work in telecommunications pertains to the widespread transition towards 5G (Li et al., 2017; Fernández Maimó et al., 2018; Alawe et al., 2018; Le et al., 2018; AlQerm and Shihada, 2017; Balevi and Gitlin, 2017).

6.3.5. 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 (Qi et al., 2017). 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 (Azadeh et al., 2014) and car parks (Sasan et al., 2018).

Where uncertainties are in outputs, unsupervised learning can assist in identifying relationships and clusters in a given dataset without prior knowledge of any links between data. This has been exploited for numerous infrastructure applications. Reinforcement learning is an inherently iterative approach, thus lends itself well to dealing with uncertainty, and has seen increased uptake in recent years. Applications have included improving energy efficiency in vehicles (Qi et al., 2017) and routing in telecommunication networks (Yu et al., 2018).

6.3.6. 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 body of work in this review is very restricted in its consideration of interlinkages and interoperability. The limited recognition of relationships and dependencies between systems is evident in a review of the water–energy nexus (Zaidi et al., 2018). 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. 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 (Geem, 2011; Al-Ghandoor et al., 2012; Murat and Ceylan, 2006), and other have considered the integration of electric vehicles into the smart grid (Rigas et al., 2015).

6.3.7. 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. Illustrating the temporal scalability achieved by research to date, one paper predicting energy consumption at building level was able to produce forecasts for 15 min, hourly, daily, weekly, or yearly intervals, at resolutions ranging from one minute to weekly, using 47 months of sampled data (Mocanu et al., 2016). In different sectors, forecasting across a span of several years is not uncommon.

Additional temporal elements to consider are training and operating speeds, which are particularly pertinent to real-time applications. 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 (Stojanovic et al., 2019).

6.3.8. Flexibility

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 areas. For example, energy demand has been estimated both at building level (Robinson et al., 2017; Mocanu et al., 2016) and for the whole urban area of Sydney (Johannesen et al., 2019). 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 (Zorzi et al., 2015), including intrusion detection (Zhang and Zhu, 2018; Abubakar and Pranggono, 2017), QoT (Samadi et al., 2017) and traffic forecasting (Alawe et al., 2018). 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.

6.3.9. Feasibility

Machine learning techniques, particularly deep learning methods requiring large datasets, have the potential to be very computationally expensive. While model accuracy is important, run-speed, especially as compared to alternative techniques, is often also a very significant factor (Bui et al., 2020). While a few papers allude to such reasons as justification for selecting one method over another, feasibility is rarely considered beyond this, 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 (Aydin et al., 2013). As regards technical feasibility, one of the core requirements of machine learning systems is access to sufficient training datasets.

6.3.10. Presentation and communication

As journal or conference papers were selected for this review, the quality of written communication was high across the board. A range of figures and graphs were used to aid understanding, with comparative studies often using graphical methods to highlight the differences between different models or techniques (Casas et al., 2017). As mentioned earlier, a substantial number of papers also used case studies to demonstrate their findings.

6.3.11. Comparison

The papers 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 papers have either compared their work against 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 (Casas et al., 2017; Hagenauer and Helbich, 2017). An important caveat to this is that comparative indicators have been overwhelmingly technical in nature. While this is a valuable gauge of ability, 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. 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 representation. The vast majority of papers attempting comparison give each method an identical dataset, which can span significant geographic and temporal ranges. Examples include forecasting for entire cities or regions (Ren et al., 2018; Zhang et al., 2017), and accident prediction based on years, or even decades, of data (Murat and Ceylan, 2006).

6.3.12. Vulnerability

The vulnerability of infrastructure systems concerns their susceptibility to both deliberate attacks and a variety of accidental causes of failure. As detailed earlier in this review, numerous papers have applied 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 (Meti et al., 2017; Abubakar and Pranggono, 2017; Tang et al., 2016). While papers concerned with non-deliberate system failure are often less explicit in their discussion of vulnerability, it could be reasoned that there are far more variables contributing to accidental failure, making the breadth of this research much greater. There are specific instances of research focusing on non-deliberate failures, including the use of machine learning techniques for fault diagnosis in high-speed rail (Yin and Zhao, 2016).

The fact that supervised machine learning techniques rely heavily on access to comprehensive training data is important in the discussion of vulnerability. 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 threshold beyond which behaviour is considered abnormal and flagged (Ashraf and Latif, 2014). Other techniques have begun to be developed (Veres and Moussa, 2019), although more work in this area would be beneficial, particularly outside of the field of telecommunications.

6.3.13. Action-oriented approach

While a number of papers have presented frameworks (Bedi and Toshniwal, 2019; Wang et al., 2016), and others have offered case studies as practical examples (Xu et al., 2019a; Azadeh et al., 2014), no papers reviewed in this work have included a formal action plan for system-wide implementation. It is worth noting, however, that much of the research described in this paper has been 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.

6.3.14. Summary

Infrastructure systems are inherently complex, and so it is promising that elements contributing to complexity – uncertainty management, interlinkages, vulnerability, and flexibility – have all been 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 (Kubat, 2017b). 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 solutions presented 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 have been outperformed 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 (Stojanovic et al., 2019). 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.

7. Further work

This work was 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 identified 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 8 would benefit from further consideration in future research. For example, having identified a gap in literature that takes an action-orientated approach, future work could seek to bring together the findings of research covered in this paper 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.

8. Conclusion

This paper reviews 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 capacity, 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. Robotics is another branch of AI that is yet to be fully exploited in infrastructure. While the potential of fully autonomous robots in several infrastructure environments has been identified, existing robots in reported infrastructure research are largely short of autonomous. Some of the most exciting examples of intelligent robots in infrastructure to date incorporate computer vision or machine learning techniques, and other sectors could benefit from research into inspection of water and electrical infrastructure by AUVs and UAVs respectively.

While research covered in this review ranges in comprehensiveness, AI techniques such as fuzzy logic allow input variables with uncertainties to be incorporated into the various indicators included in comprehensive papers. The dependence of many machine learning tools on the training data available means that, provided sufficient data is available, they can be adapted to suit a range of temporal scales, geographic areas, and network sizes. The data-driven nature of such tools also allows for a context-driven approach, with case studies often used to demonstrate effectiveness. Where research is lacking, however, is in incorporating broader infrastructure targets. Minimal work has sought to account for strategic goals in the problem formulation stage, while no work to date has put together a structured action-plan based on its findings. Though AI has been effectively applied to a number of highly specific purposes, there remains work to be done to incorporate it into an interconnected systems approach.

AI methods will have a valuable role to play in the burgeoning fields of distributed intelligence and the 'Internet of Things'. Knowledge representation will prove significant as sensors from a wide range of networks will need to be structured within a complex and interconnected knowledge base. As sensor networks provide increasing volumes of data, edge networking is an attractive solution to scalability concerns, with machine learning methods able to convert vast amounts of data into small packets of information for transmission (Garofalo et al., 2020). AI techniques can reason from data provided by sensor networks in the absence of human operators, which can contribute to the development of autonomous anticipatory and self-healing networks. Such capabilities can massively improve network resilience under growing uncertainty and are needed if interconnected systems are to effectively respond to the pressures of increasing populations, digitalisation, and complexity.

CRediT authorship contribution statement

Lauren McMillan: Methodology, Investigation, Data curation, Writing – original draft, Visualization. **Liz Varga:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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