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# Monitoring systems for $CO_2$ transport pipelines: a review of optimization problems and methods

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**Abstract**

Carbon Capture and Storage (CCS) is a key technology for reducing anthropogenic greenhouse gas emissions, in which pipelines play a vital role in transporting $CO_2$ captured from industrial emitters to geological storage sites. To aid efficient and safe operation of the $CO_2$ transport infrastructure, robust, accurate and reliable solutions for monitoring of pipelines transporting industrial $CO_2$ streams are urgently needed. This paper reviews the literature on monitoring objectives, optimization problems and mathematical algorithms developed for pipeline systems transporting water, oil and natural gas, and identifies the problems and methods relevant to monitoring of the future $CO_2$ pipelines and pipeline networks for CCS. The impacts of physical properties of $CO_2$ and complex designs and operation scenarios of $CO_2$ transport on the pipeline monitoring systems design are discussed. It is shown that the most relevant to liquid and dense phase $CO_2$ transport are the sensor placement optimization methods developed in the context of detecting leaks and flow anomalies for water distribution systems and pipelines transporting oil and petroleum liquids. The monitoring solutions relevant to flow assurance and monitoring impurities in $CO_2$ pipelines are also identified. Optimizing the $CO_2$ pipeline monitoring systems against several objectives, including the accuracy of measurements, the number and type of sensors, and the safety and environmental risks, is discussed.

*Keywords:* Pipeline transport network; monitoring systems; optimization; sensor placement; algorithms

## 1. Introduction

Global warming and climate change caused by increasing anthropogenic emissions of greenhouse gases, especially carbon dioxide ($CO_2$), into the atmosphere, represent urgent challenges to humanity [1], [2]. In 2022, the annual emissions of $CO_2$ have reached a new record, while global energy-related $CO_2$ emissions grew by 0.9% or 321 Mt, reaching a new high at *ca* 36.8 Gt [3]. To urgently address the global warming, Carbon Capture and Storage (CCS) has been proposed as an effective way of mitigating the carbon emissions and heading towards the clean energy sources [4]. However, despite the large momentum gained in demonstration of $CO_2$ capture and storage in a number of pilot CCS projects (e.g., [5]), the large-scale CCS deployment is significantly hampered by the lack of $CO_2$ transport infrastructure connecting industrial $CO_2$ emitters with the geological sequestration sites (e.g., [6], [7]). These transport solutions, given the large quantities of $CO_2$ and long distances involved, are expected to largely rely on pipelines [8]. However, despite the accumulated experience in design and operation of pipeline systems in general and over 40 years of history of $CO_2$ pipeline transport for Enhanced Oil Recovery (EOR) [9], implementing the $CO_2$ transport infrastructure for CCS at scale requires, apart from overcoming financial and business barriers, also addressing a number of technical challenges [10].

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**Nomenclature**

| | |
|---|---|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| AMGA | Adam-mutated Genetic Algorithm |
| CCS | Carbon Capture and Storage |
| CSO | Combined Sewer Overflows |
| DT | Digital Twin |
| EOR | Enhanced Oil Recovery |
| GA | Genetic Algorithm |
| IPCC | Intergovernmental Panel on Climate Change |
| MILP | Mixed-Integer Linear Programming |
| ML | Machine Learning |
| MOEA | Multi-Objective Evolutionary Algorithm |
| PSO | Particle Swarm Optimization |
| RTC | Real Time Control |
| SCADA | Supervisory Control and Data Acquisition |
| WDS | Water Distribution System |
| WSN | Wireless Sensor Network |

Figure 1 shows schematically the special features of $CO_2$ transport for CCS and the various design and operation challenges for the $CO_2$ pipeline systems. An important distinctive feature of $CO_2$ is that it can cause asphyxiation when present in the air in concentrations above ca 7% [11, 12]. A recent accidental rupture of $CO_2$ pipeline in Mississippi, USA demonstrated significant risks posed by $CO_2$ pipelines to nearby population [13]. For this reason, similar to pipelines transporting other hazardous fluids (e.g., flammable fluids and natural gas, and crude oil), the Quantitative Risk Assessment (QRA) of $CO_2$ transport facilities is an important requirement. In addition, as indicated in Figure 1, $CO_2$ pipeline systems involve collecting impure $CO_2$ streams from various emission sources. These streams may contain certain impurity components, which may have their own safety hazards (e.g., due to their toxic nature) or pose risks to the integrity and operation transport and storage facilities (e.g., due to their corrosive nature), and hence their concentrations should be limited [14]. Impurities in $CO_2$ streams can also increase the risks of running ductile or brittle pipeline fractures [14].

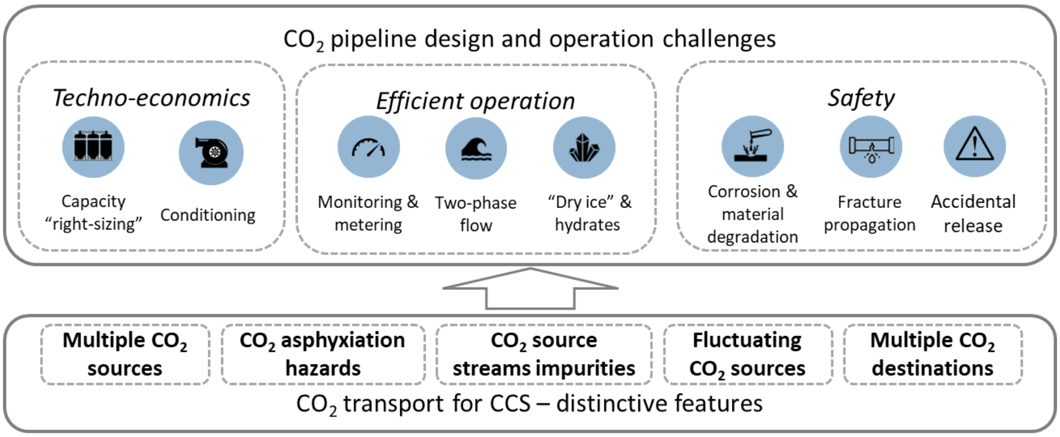


Figure 1. $CO_2$ pipeline system design and operation challenges.

Compared to water, crude oil and other liquid petroleum products, $CO_2$ has relatively low boiling points, which means that decompression of liquid $CO_2$ (which is the most economical phase for pipeline transportation) to pressures below its saturation conditions can lead to two-phase flow, which is undesirable from the flow assurance perspective. Given relatively low critical pressure and temperature of $CO_2$ (*ca* 73.8 bar and 31.1 $^oC$), $CO_2$ can also be transported as supercritical fluid, which is also attractive given its relatively high density and low viscosity. However, the supercritical $CO_2$ also has relatively high compressibility and thermal expansion coefficient compared to other pipeline transport liquids (e.g., water, crude oil and petroleum products), which may in turn induce transient flow oscillations in long pipelines following emergency valve closure or pump shut-down [15].

Similar to many other pipeline systems (e.g., consumer gas distribution networks, water supply networks, and sewage and drainage systems), where inlet or outlet flow conditions (particularly pressure and flow rate) vary over time, $CO_2$ pipeline systems should also be designed to accommodate transient operations, resulting, e.g., from short-term fluctuations in the flow rates of $CO_2$ captured from industrial sources.

Another distinct feature of $CO_2$ pipeline systems is the collection type of $CO_2$ networks, where many sources are connected to a site (or possibly several sites) for geological storage of $CO_2$ via a tree-type structure (similar to urban drainage systems) and long high-pressure trunk lines (similar to oil and gas transmission lines). While domestic potable water and natural gas networks may also have a tree-type structure, unlike $CO_2$ transport systems, they are distribution networks and commonly include loops where some nodes are connected to each other via two or more paths.

Figure 1 also shows a number of challenges associated with the economic, safe and efficient design and operation of $CO_2$ transport systems for CCS. Importantly, given large quantities envisaged for $CO_2$ transport in CCS, significant operation costs of $CO_2$ infrastructure and safety hazards associated with $CO_2$, the next generation $CO_2$ pipeline transport systems will require implementing monitoring and control strategies [16, 17]. Given the complexity of $CO_2$ transport networks, optimizing their monitoring and control will aid accurate flow measurements, enhance early detection of potential issues, e.g., due to upset operation, phase transition, corrosion, and leaks, and reduce the operational costs of $CO_2$ transport. In this context, there is considerable interest in adopting the expertise and methods developed for the monitoring of pipelines transporting non-$CO_2$ fluids to the emerging field of $CO_2$ pipeline transportation.

To this end, this paper is aimed at a systematic review of practical challenges and cutting-edge research on optimal design of monitoring systems and strategic placement of sensors for onshore pipelines and pipeline networks. Section 2 identifies the monitoring objectives and techniques for pipelines transporting various gases and liquids, including $CO_2$. Section 3 reviews the current status of research on sensor placement in pipelines and pipeline networks, with a systematic description of the relevant optimization problems and solution algorithms. Section 4 discusses the potential applications of the reviewed optimization problems and related algorithms to the design of $CO_2$ pipeline monitoring systems, including the necessary adaptations for effective technology transfer. Finally, Section 5 summarizes the study findings, highlights the need for $CO_2$ pipeline monitoring systems, and suggests directions for future research.

## 2. $CO_2$ pipelines monitoring objectives

Monitoring of $CO_2$ pipelines is based on the principles and guidelines developed for pipelines transporting other fluids, where monitoring is a key part of the pipeline management that includes three main elements [16]:

- the pipeline integrity management, which is aimed at detecting damage and failures of the pipeline infrastructure, potentially posing threats to the pipeline operation, the public or the environment,
- contamination control to ensure the quality of fluid delivered to a customer, and
- fiscal metering for commercial purposes (custody transfer).

The pipeline monitoring objectives address detecting and locating pipeline failure (including leaks and ruptures), and identifying any flow anomalies that can be detrimental either to the pipeline efficient and safe operation (i.e., scenarios that may lead to the pipeline system failure) or the quality of service or properties of the delivered fluid (e.g., the fluid flowrate, pressure and temperature, composition, and the amount of impurities and contaminants).

Pipeline failures, including the pipeline leaks and ruptures, happen due to the pipeline material degradation (e.g., erosion and internal or external corrosion), impacts of natural forces (such as landslides, earthquakes, e.g., [13], [18]) or third-party damage (e.g., upon excavation, vandalism or theft activity) (see, e.g., [19] and [20]). Undetected pipeline leaks may evolve into larger ruptures and bursts leading to catastrophic consequences and fatalities (e.g., [21], [22]).

To identify and locate the pipeline failures, periodic *inspections* (e.g., visual external inspections (patrolling) and using smart pipeline inspection gauges to assess the pipeline internal conditions) and pipeline exterior and interior *monitoring* techniques are applied (see e.g., [23-28]).

In particular, detecting and localizing pipeline leaks has attracted much attention, with a number of effective techniques and methods proposed in the past few decades [29-33], including Computational Pipeline Monitoring (CPM) that detects leaks by examining anomalies in the flow by comparing the real-time measurements of the flow with predictions by a digital model [34]. Furthermore, leak detection and localization can be an integral part of the pipeline control and emergency shutdown system (see e.g., [35-38]) aimed at mitigating the consequences of pipeline failure – minimizing the damage to the environment or escalation of safety hazards [39]. Supervisory Control And Data Acquisition (SCADA) system provides a platform for collecting in real-time the measurements of pressure, temperature and flowrate of the transported fluid (typically, taken at locations of compressors, pumps, valves and metering stations) and passing this information to the pipeline operator (see, e.g. [16, 34, 40, 41]).

The existing experience in operation and the records of accidents for $CO_2$ pipelines show that failure rates of $CO_2$ pipelines are similar to those for hydrocarbon pipelines [42], with ca 7% of accidents reported in the PHMSA database during the period from 2010 to 2017 being identified using computerized monitoring systems [43]. While $CO_2$ pipeline ruptures can happen (as in the recent accident near Satartia, Mississippi, USA [18]) and may have catastrophic consequences in case of pipelines passing through populated areas, they are comparatively less statistically frequent than ruptures in hydrocarbon pipelines [42]. At the same time, $CO_2$ pipelines are more prone to smaller size leaks than the hydrocarbon pipelines [44, 45], highlighting the need for the leak detection and monitoring of $CO_2$ pipelines.

Previously, CPM systems were not required for leak detection in $CO_2$ pipelines, mainly because of their technical complexity, and instead the pressure point measurements and regular pipeline visual inspections were recommended as simple monitoring techniques [46]. However, more recently, integrating CPM systems with SCADA and Digital Twin (DT) technology predicting the system's future states using the real-time measurements [47-50], has been proposed as a solution that can potentially improve the monitoring and operational integrity of $CO_2$ pipelines and networks [51-53].

Apart from leak detection and localization, operation of $CO_2$ pipelines requires careful monitoring of flow parameters to control the threats associated with [16]:

- the free water content and concentration of other impurity components, which may pose a risk of pipeline internal corrosion, hydrate formation (especially for offshore pipelines), transition to two-phase flow upon changes in the pipeline pressure, or additional safety hazards (e.g., when toxic components such as $H_2S$ or $SO_2$ are present).
- the pressure variation during start-up, shut down, depressurization and normal operation conditions that may pose risks of the pipeline overpressure and impact the water solubility in dense phase $CO_2$.
- the temperature variations during start-up, shut down and normal operations that may alter the $CO_2$ thermodynamic state, the density of $CO_2$ fluid and the pipeline transportation capacity.

Also, measuring the flowrate and composition of $CO_2$ streams is important to meet the product specifications for custody transfer – to ensure the quantity and quality of the $CO_2$ delivered by the pipeline operator. The principles and methods of measuring flowrates in pipelines transporting gases and liquids are well established (see, e.g., [54]). However, measuring $CO_2$ flowrate presents a number of challenges, which can be associated with (a) unique physical properties of $CO_2$, e.g., the acoustic attenuation posing a challenge for using ultrasonic flow meters, the presence of impurities that can affect the thermodynamic properties and phase equilibria, (b) measurement uncertainties due to pressure or temperature variations in the pipe, and (c) the lack of standards and calibration facilities for industrial use [52, 55, 56].

While sampling is typically used for offline composition analysis in batch transportation, $CO_2$ pipeline transport calls for online near real-time measurements of the concentration of $CO_2$ and major impurities. The technologies for monitoring and detecting the flow contaminants, including the offline, online and real-time methods, have been developed with application to water supply and distribution systems (see, e.g., [57, 58]). Also, measuring impurity components has recently attracted attention in the context of the transportation of hydrogen via pipelines that were previously used for transporting natural gas [59]. As pointed out by Chinello et al. [55], the adaptation of the existing methods to $CO_2$ transport is technically challenging due to factors such as the transient nature of the flow, which requires frequent sampling, and also small amounts of the impurity components that require high precision of measurements.

## 3. Optimization of pipeline monitoring systems

As explained in Section 2, the pipeline monitoring systems serve various aims and objectives. Moreover, the pipeline monitoring and control system should be efficient, reliable, and robust to ensure, e.g., rapid leak detection and emergency response, accurate measurement and regulation of flow parameters, low energy consumption and cost-effectiveness of the pipeline operation. To meet these criteria and any additional constraints associated with, e.g., cost limitations or specific types of solutions to be implemented in a project, the pipeline monitoring system can be designed by solving a mathematical optimization problem where the above criteria represent the optimization objectives, system constraints and decision variables (i.e., the design parameters that can be changed to achieve the optimal solution meeting the optimization objective(s), e.g., the number, position or type of sensors), as schematically illustrated in Figure 2.

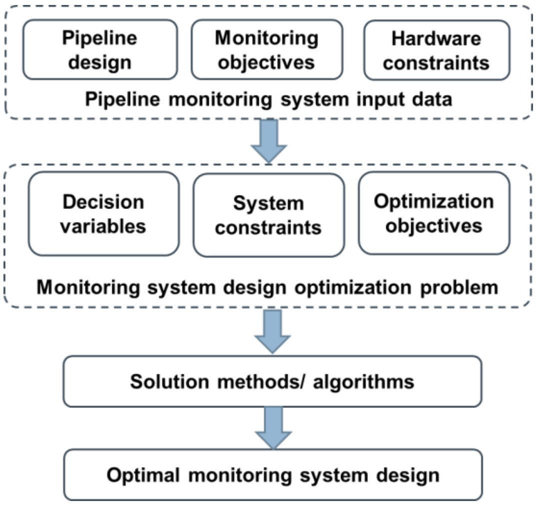


Figure 2. Methodology for optimizing pipeline monitoring systems.

While currently optimizing monitoring systems for $CO_2$ transport has received very little attention in the literature (with the exception of the study by Kim et al., [60]), a significant amount of research has accumulated on developing optimization models and methods for the design of monitoring systems for pipelines and pipe networks transporting water, natural gas, oil and petroleum liquid products. The rest of this section provides a systematic literature review of the pipeline monitoring design optimization problems studied in the past in the context of (1) leak detection and localization, (2) flow measurements, (3) fluid quality control, and (4) improving energy efficiency and cost-effectiveness of the monitoring solutions.

### *3.1 Leak detection and localization*

Leak detection and localization are two of the most common objectives in pipeline integrity management. Meeting these objectives requires instrumenting the pipeline to detect changes in pressure, temperature or flowrate, and using flow simulation techniques (e.g., CPM) to trace back these changes to the leak location [32, 33]. The accuracy of the adopted technique depends on the spacing between the transducers, the uncertainty of pressure and flowrate measurements and the level of noise/noise filtering algorithms adopted. As such, optimization of leak detection/

localisation systems typically concerns the sensor placement, aimed at strategically positioning several sensors to maximize leak detection sensitivity and accurately locate the leak.

Leak detection and localization methods have been largely developed with application to water distribution systems (WDS). For example, Casillas et al. [61] applied an integer programming approach to describe the problem of sensor placement for leak localization, which involved minimizing the number of non-isolable leaks to meet the isolability criteria introduced to distinguish between two possible leaks. The non-linear optimization problem was solved using Genetic Algorithms (GA) [62]. Similarly, Shiddiqi et al. [63] developed a GA-Sense method for sensor placement strategy by considering flow patterns to maximize leak detection and localization capabilities. They utilized time-series data to find strategic sensor locations to identify abnormal flow patterns indicative of leaks. GA and its variations have become popular for solving non-linear sensor placement optimization problems [64]. Another sensor placement method, developed by Ribeiro et al. [65], involves optimizing the number of the pipes to inspect, and applying TrustRank algorithm (see [66]) to refine the solution as part of sensitivity analysis. Additionally, Mixed-Integer Linear Programming (MILP) algorithm is frequently used for optimally placing sensors in pipeline systems. For instance, Xing et al. [67] studied the problem of sensor placement for robust burst (refers to sudden pipe rupture and break) event identification under sensor data uncertainties and information uncertainties inferred from data; the MILP method was applied to maximize the detection of the burst events under both limited or unlimited budgets. Recently, with the development of computational science and big data technology, the data-driven and Artificial Intelligence (AI) methods, including statistical inference methods, have become more frequently applied to further optimize leak detection monitoring performance [68-71], as these methods can save computational costs for flow simulations.

For hydrocarbon pipeline transport systems, there are also various studies focusing on sensor placement for leak detection. For example, Zan et al. [72] introduced a multi-objective sensor placement optimization method for low-pressure residential gas distribution networks. The objectives included minimizing the time-to-detection, maximizing the sensitivity to the anomalies, and minimizing the impact propagation by the leaks. The multi-objective problem was formulated for a vector of decision variables and then solved using five different algorithms: (1) greedy, (2) greedy randomized adaptive search procedure, (3) Non-dominated Sorting Genetic Algorithm II (NSGA-II), (4) FrameSense, and (5) Particle Swarm Optimization (PSO), among which PSO yields the sensor configuration with the lowest design cost and the computational time. Kim et al. [73] employed the Adam-Mutated Genetic Algorithm (AMGA) to optimize sensor placement to detect ruptures subject to uncertainties of the simulation models. Sun et al. [74] accounted for leak scenarios probability and detector reliability in the gas detector placement problem, which was solved using a stochastic programming (SP) optimization method.

In the transportation of crude oil and petroleum liquids, leak detection is one of the most practically relevant monitoring objectives. In mathematical terms, the problem is commonly described as the optimal sensor node placement, which can be solved using, e.g., the cluster-based heuristic algorithms [75, 76].

The specific choice of the algorithms for solving the above-mentioned optimization problems largely depends on the optimization variables and constraints, as well as the required accuracy of the solution, and the computational runtime. For example, MILP and MINLP techniques are used for optimal sensor placement for leak detection when specific system constraints and operational requirements are explicitly modelled and incorporated into the optimization process [67, 72, 73, 77]. On the other hand, genetic algorithms are designed to tackle large-scale, highly complex problems, especially those involving non-linear objectives, and are widely used to solve sensor placement optimization problems for water distribution networks [60, 63, 78] and long-distance oil transmission pipelines [79, 80]. Additionally, advanced techniques such as data-driven approaches, Artificial Intelligence (AI) and Machine Learning (ML) methods are attractive to save licensing and computational cost when flow simulations are needed and were recently applied to optimize sensor placement for leak detection and localization in water and natural gas pipeline systems [49, 69, 70].

### *3.2 Flow rate measurement*

Accurate measurement of flow rate is essential for pipeline transport systems, and optimization methods are being developed to achieve the best flow rate measurement performance. Particularly challenging is the accurate real-time measurement of flowrates over a wide range of operating conditions, including possible multiphase flow regimes, in pipelines transporting petroleum-derived liquids [81]. Specific challenges with flowrate measurements in single-phase pipeline transport can be related to distinct operational features of the gas and liquid transport systems. In particular, gas pipelines commonly operate in transient mode, with line packing utilized to compensate for imbalances in the inlet and outlet flowrates. Control of the gas line operation requires careful measurement of the operating pressure – to ensure it stays within the limit between the maximum and minimum allowable limits, and the flow rate – to meet the natural gas demand. In pipelines transporting liquids, e.g., crude oil transmission lines, monitoring and control of the fluid temperature is an important part of flow assurance to ensure low viscosity of liquid for smooth operation and minimising the pipeline hydraulic losses. As such, in general, flowrate monitoring is part of a complex monitoring and control system that involves measurement of flow parameters (the flow rate, pressure and temperature) at various locations along the pipeline. Some recent studies have focused on improving the accuracy and reliability of the flowrate measurements in pipelines. For example, Ferrari and Pizzo [82] developed a virtual flow meter for highly transient flows in pipelines transporting liquids. In another study, van Westering and Hellendoorn [83] constructed a constrained non-linear integer programming optimization model to determine locations where flow meters should be placed in a large natural gas distribution network to aid accurate estimation of gas consumption under uncertain demand.

### *3.3 Fluid quality and impurities monitoring*

Given that water quality and the amount of contaminants and residual disinfectants present in water supply pipelines are critical for public health, extensive research has focused on optimizing measurement of composition and detection of contaminants in WDS. Preis et al. [84] applied the Non-dominated Sorted Genetic Algorithm NSGA II to solve a multi-objective optimization problem of collocating the pressure and water quality measurement points in WDS, showing that using sensors with dual capabilities could significantly reduce the monitoring system expenses. Similarly, He et al., [85] proposed using a Multi-Objective Evolutionary Algorithm (MOEA) to solve a bi-objective optimization problem of sensor placement, aiming to minimize the contamination detection time while maximizing the detection probability. Cardoso et al. [86] further extended the list of optimization criteria for sensor placement to include the minimum detection time, the minimum exposed population, the minimum consumption of contaminated water before detection, and the maximum detection probability. This multi-objective problem was solved using NSGA-II algorithm [87] and applying K-means clustering unsupervised ML algorithm [88] for Pareto front post-processing. Recently, coupling the Gas Chromatography (GC) and the Optical Feedback Cavity-Enhanced Absorption Spectroscopy (OFCEAS) has been recommended as the optimal solution that minimizes costs and achieves high accuracy – to meet the high purity requirements for hydrogen transport [89].

### *3.4 Energy efficiency and cost-effectiveness of monitoring system*

Energy saving and cost-effectiveness of sensor operations are two key criteria applied in optimizing sensor placement in pipeline systems to ensure their long-term monitoring efficiency. Strategically placing sensors reduces the energy consumption of devices, prolonging a network's operational lifetime and minimizing maintenance needs, especially in remote areas, and can also reduce the total monitoring costs.

Using wireless sensors becomes attractive for pipeline monitoring systems. The problem of optimal design of a Wireless Sensor Network (WSN) in long oil transmission pipelines was recently studied by Elnaggar et al. [80]. The optimization sought maximizing pipe coverage (i.e., the length of pipelines being monitored) and minimizing overall costs of the monitoring system. Varshney et al. [90] also proposed an efficient sensor placement strategy for managing various pipelines (air-conditioner, water, gas, oil) inside a large smart building using the Lion Optimization Algorithm (LOA). Recently, advanced machine learning methods, incorporating reinforcement learning [91] and Q-learning algorithms [92], were used by Rahmani et al. [93] to solve the sensor placement problems maximizing the coverage of oil pipelines while also taking into account other optimization criteria, including the energy consumption and the network lifetime.

## 4. Recommendations on optimizing the $CO_2$ pipeline monitoring systems

Table 1 summarizes the optimization problems and the corresponding solution methods developed in the context of monitoring pipelines transporting fluids other than $CO_2$, as reviewed in Section 3. The pipeline monitoring objectives that appear in the table can be grouped into three categories: (1) the leak detection and localization, (2) measurement of the flow rate, pressure and temperature, and (3) the flow quality and components monitoring. The decision variables represent the monitoring system design parameters that can be changed to achieve the solution meeting the optimization objective(s). Among the listed decision variables, the sensors' positions are most used in the sensor placement problems optimizing the number of sensors, pipeline coverage, accuracy, time and probability of detection of leaks and flow anomalies, power consumption by wireless sensors, etc. The table also lists mathematical methods and algorithms applied for solving the optimization problems, the specific choice of which is generally governed by the type of decision variables and constraints (discrete/continuous, convex/nonconvex, linear/nonlinear, deterministic/stochastic), the number of optimization objectives (single-/multi- criteria), and the search for local or global optimum. In the following, the relevance of optimization problems and methods listed in Table 1 to the $CO_2$ transport system is discussed for the different monitoring objectives.

### *4.1 Leak detection and localization*

The experience in optimizing sensors for leak detection and localization in water distribution systems and oil pipelines can generally be applied to leak detection in $CO_2$ pipelines, especially considering the expected large demand for transporting $CO_2$ in liquid/ dense phase. As can be seen in Table 1, the optimization can target single or multiple objectives, e.g., to determine a trade-off between the number of sensors and the detection accuracy of sensors placed at different locations, with a wide choice of potential algorithms for solving these problems, as discussed earlier in section 3.1.

While there are no examples of optimizing monitoring systems for leak detection in $CO_2$ pipelines, recently Kim et al [60] applied Deep Learning methods to detect flow anomalies due to leaks and hydrates accumulation in $CO_2$ pipelines.

Given the potential hazard of a heavy gas $CO_2$ cloud that may form upon accidental puncture or rupture of $CO_2$ pipelines [11], accounting for nearby population density should be considered as a key factor when optimizing $CO_2$ pipeline monitoring and control systems.

### *4.2 Flow measurement*

As can be seen from Table 1, in the context of flow measurements, the problem of optimal sensor placement has been studied for natural gas networks [83], where a constrained non-linear integer programming optimization model was constructed to determine locations of flow meters for accurate estimation of the overall gas consumption under fluctuations in demand. This approach can potentially be useful for monitoring flowrate in networks collecting fluctuating $CO_2$ sources.

Also, some studies focus on optimizing the accuracy of the flowrate measurements in pipelines. For example, as mentioned earlier in section 3.2, Ferrari and Pizzo [82] developed a virtual flow meter to aid accurate estimation of mass flowrate based on the pressure measurements in highly transient flows in pipelines transporting liquids.

Monitoring and improving the accuracy of flow measurement has recently attracted attention in the context of $CO_2$ pipeline transportation. In particular, Kim et al [60] applied Deep Learning to detect anomalies in the flow of dense phase/ super-critical $CO_2$ in a long pipeline with fluctuating inlet flow conditions. Also, given the low boiling point of $CO_2$, two-phase flow may emerge in some scenarios, e.g., during the start-up or shut-down or partial venting of a pipeline. To provide accurate flow measurements for the flow assurance in these scenarios, Jeong et al. [96] have recently applied the ML Artificial Neural Network (ANN) algorithm that recognizes two-phase flow patterns.

Table 1. Monitoring systems optimisation problems and algorithms relevant to various pipeline transport systems.

| Transported fluid & network type | Monitoring objective(s) | Decision variable(s) | Optimization objective(s) | Type of optimization problem | Single/ Multi-objective | Method(s) / Algorithm(s) | Ref. |
|---|---|---|---|---|---|---|---|
| **Water distribution networks** | Loss quantification; leak localisation | Hydraulic model parameters | Maximum accuracy of water loss detection and localization | Nonlinear optimization problem | Single objective | GA | Wu and Sage [94] |
| | Leak localization | Sensors positions, leak/burst localisation parameters | Maximum accuracy of leak localization | Nonlinear optimization problem | Multi-objective | Data-driven, multi-objective evolutionary algorithm | Boatwright [95] |
| | | Positions of sensors | Minimum number of sensors; maximum accuracy of leak localization | Nonlinear optimization problem | Single objective | ML classification and feature selection | Madbhavi et al. [70] |
| | Water quality and contamination detection and localization | Sensors positions | Minimum number of sensors, detection time and population affected; maximum probability of detection | Nonlinear optimization problem | Multi-objective | NSGA | He et al. [85], Cardoso et al. [86] |
| **Urban drainage collection networks** | Water quality and the presence of pathogens | Sensors positions | Minimum number of sensors; Maximum network reliability and sensor nodes centrality | MILP or MINLP (depending on the problem formulation) | Single objective | SCIP algorithm (spatial branch-and-bound algorithm); Complex Network Theory | Simone et al. [96] |
| **Oil transmission pipelines** | Temperature and pressure monitoring | Sensor positions | Minimum power consumption by sensors | MILP | Single objective | Greedy algorithm | Guo et al. [76] |
| | Leak localization | Activity time of sensors | Minimum sensor's power consumption; Maximum pipeline coverage | Nonlinear optimization problem | Single objective | Reinforcement Learning Algorithm (AI machine learning) | Rahmani et al. [93] |
| **Natural gas transmission lines** | Leak detection and fault diagnostics | Sensor positions | Maximize the detected number of contaminant points | MILP | Single objective | Deep learning | Liang et al. [49] |
| **Natural gas distribution network** | Network flow simulation | Sensors positions | Maximum accuracy of the measurement across entire network | Constrained MINLP | Single objective | Greedy algorithm, GA | van Westering and Hellendoorn [83] |
| **Low-pressure gas distribution networks** | Detecting flow anomalies | Sensors positions | Minimum time to detection, Maximum sensitivity and impact propagation | MINLP | Multi-objective | Greedy, GRASP, NSGA II, FrameSense and PSO algorithms | Zan et al. [72] |

### 4.3 Impurities monitoring

As can be seen in Table 1, sensor placement for detection of contaminants has received significant attention in the context of monitoring of WDS (see, e.g., Cardoso et al. [86]). However, the optimization problems studied for WDS have little relevance to $CO_2$ pipeline transport because the two systems are rather different in their design and operation, and the impurities monitoring serves different objectives. In particular, in $CO_2$ transport networks, which have a tree-type layout, the impurities originate at the network sources. To ensure the $CO_2$ streams compatibility with the specifications for transport and storage, the $CO_2$ impurities need to be measured at the network sources, and possibly at some locations in the network, e.g., collection hubs, where several streams are merged, or points of transfer to offshore transport/ injection systems. In contrast to $CO_2$ transport networks, the WDS networks can include loops and grid elements, and flow contamination may happen at various places across the network (e.g., consumer connection points, hydrants, and pipeline cracks). As such, contaminants monitoring is conceptually much more complex for WDS than for $CO_2$ collection networks.

Nevertheless, adapting the flow models for component tracking used in sensor optimization studies for WDS [86] can be useful for facilitating the composition monitoring in $CO_2$ pipeline networks.

## 5. Summary and directions for future studies

The large-scale deployment of Carbon Capture and Sequestration (CCS) will require using pipelines to transport large quantities of $CO_2$ from industrial emitters to geological storage locations. Accurate and reliable monitoring and control of $CO_2$ transport systems will be crucial for their reliable, safe and economic operation. Given new challenges brought by $CO_2$ transport for CCS, and the significant experience accumulated in operation of pipelines transporting water, oil and natural gas, there is a strong interest in adapting the existing monitoring solutions, design practices and methods to $CO_2$ pipeline transport. This paper provided a systematic literature review of the cutting-edge research on optimization of monitoring systems for leak detection and localization, flow metering, and fluid quality and components tracking in pipelines transporting various fluids, that can potentially be useful for $CO_2$ pipeline monitoring. The key findings and recommendations from the study can be summarized as follows:

- Methods of computer-based leak detection and localization, and also optimal placement of monitoring sensors developed for pipelines transporting liquids (including water distribution systems and pipelines transporting crude oil and petroleum liquids) are relevant to liquid and dense phase $CO_2$ transport.
- Artificial Intelligence (AI) and Machine Learning (ML) methods developed for detecting flow anomalies and leak detection in natural gas and oil pipelines can be adapted to improve flow monitoring in $CO_2$ pipelines. In particular, using ML-based anomaly detection and virtual flow metering can enhance flow measurement accuracy in scenarios of transient and two-phase flow to aid the flow assurance in the start-up, shutdown, or emergency operations of $CO_2$ pipelines.
- Adapting the flow models for components tracking, such as those developed for water distribution systems, can be useful for enhancing the composition monitoring in $CO_2$ pipeline networks. To improve the accuracy of measurement of small impurity concentrations, using optimal combinations of techniques, e.g., Gas Chromatography (GC) and Optical Feedback Cavity-Enhanced Absorption Spectroscopy (OFCEAS), as suggested for hydrogen transport, can be attractive.
- Sensor placement is the most studied pipeline monitoring optimization problem. Other optimization decision variables may include the types and combinations of sensors, and also the optimal number of sensors or monitoring points.
- $CO_2$ pipeline monitoring optimization can be described as a multi-objective optimization problem. While accuracy of measurements, the number of sensors and cost of monitoring are the most commonly employed objective functions, the risks to the nearby population and environmental impacts in the event of accidental $CO_2$ release must also be considered as part of the optimization criteria.
- Various mathematical methods and algorithms for solving the pipeline monitoring optimization problems are available. The specific choice of methods/algorithms depends on the types of the optimization model decision

variables and constraints, the number of optimization objectives, the presence of a stochastic component of the objective function and potential multiple solutions, amongst other factors.

- Currently, emerging model-based data-driven approaches and non-model-based techniques, such as deep learning, are gaining traction in optimizing the monitoring and control of various pipeline systems. These methods offer significant potential for $CO_2$ transport systems, particularly when integrated with pipeline flow simulators and Digital Twin platforms, to process large datasets covering the various pipeline operation scenarios.

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