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# A Review of Optimization Methods for Pipeline Monitoring Systems: Applications and Challenges for $CO_2$ Transport

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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 the efficient and safe operation of the $CO_2$ transport infrastructure, robust, accurate, and reliable solutions for monitoring pipelines transporting industrial $CO_2$ streams are urgently needed. This literature review study summarizes the monitoring objectives and identifies the problems and relevant mathematical algorithms developed for optimization of monitoring systems for pipeline transportation of water, oil, and natural gas, which can be relevant to the future $CO_2$ pipelines and pipeline networks for CCS. The impacts of the 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

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Academic Editors: Hongfang Lu, Shanbi Peng, Enbin Liu and Weibiao Qiao

Received: 28 May 2025
Revised: 30 June 2025
Accepted: 5 July 2025
Published: 8 July 2025

**Citation:** Xu, T.; Martynov, S.; Mahgerefteh, H. A Review of Optimization Methods for Pipeline Monitoring Systems: Applications and Challenges for $CO_2$ Transport. *Energies* **2025**, *18*, 3591. https://doi.org/10.3390/en18143591



## 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 global warming, Carbon Capture and Storage (CCS) has been proposed as an effective way of mitigating carbon emissions and heading towards clean energy sources [4]. While recently, large momentum has been 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 currently 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 still faces a number of technical challenges apart from financial and business barriers [10]. 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 a $CO_2$ pipeline in Mississippi, USA, demonstrated significant risks posed by $CO_2$ pipelines to the nearby population [13]. For this reason, similar to pipelines transporting other hazardous fluids (e.g., flammable fluids, 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 of 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].

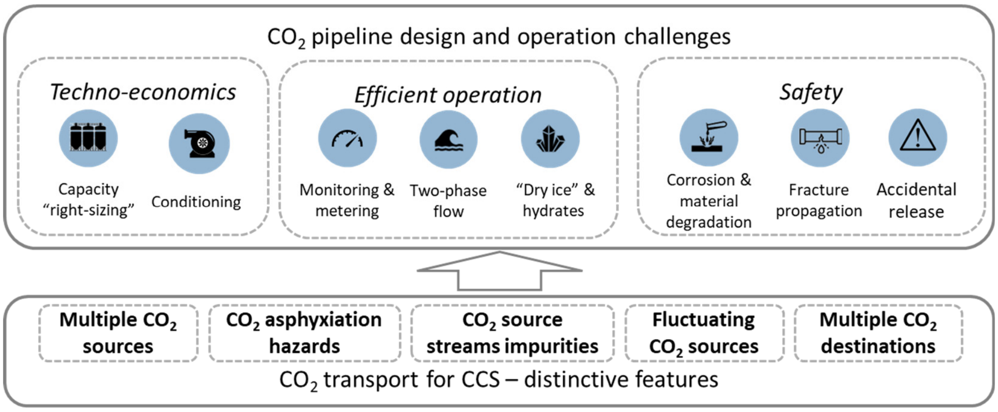


**Figure 1.** $CO_2$ pipeline system design and operation challenges.

Compared to water, crude oil, and other liquid petroleum products, $CO_2$ has a relatively low boiling point, 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 °C), $CO_2$ can also be transported as a supercritical fluid, which is also attractive given its relatively high density and low viscosity. However, compared to other pipeline transport liquids (e.g., water, crude oil, and petroleum products), the supercritical $CO_2$ has relatively high compressibility and thermal expansion coefficient, which may promote flow oscillations in long pipelines in scenarios of emergency valve closure or pump shutdown [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 conducts a structured review of practical challenges and recent research on the optimal design of monitoring systems and the strategic placement of sensors for onshore pipelines and pipeline networks. In particular:

- Section 2 describes the scope and methodology for the literature review;
- Section 3 outlines the monitoring objectives and techniques for pipelines transporting various gases and liquids, including $CO_2$;
- Section 4 reviews optimization problems and solution algorithms for sensor placement in such systems;
- Section 5 explores how the optimization methods reviewed in Section 4 can be adapted to $CO_2$ pipeline monitoring, considering specific physical and operational features;
- Section 6 summarizes the key findings and suggests directions for future work.

## 2. The Review Scope and Methodology

This review focuses on optimization-based approaches for designing monitoring systems in onshore pipelines, with particular attention to the sensor placement. The motivation comes from the monitoring needs highlighted in CCS/CCUS reports, handbooks, and industrial guidance. The goal is to summarize relevant methods and evaluate their potential for application to the monitoring systems of $CO_2$ pipeline transport networks.

Literature was searched mainly by using Google Scholar, covering peer-reviewed publications in English from 2010 to 2024. The search focused on works relevant to pipeline monitoring, sensor network design, and optimization algorithms. Both primary sources (e.g., original research articles and case studies) and secondary sources (e.g., review papers, industrial reports, and CCS handbooks) were included to ensure a comprehensive overview. The keywords were grouped according to the structure of this review:

1. $CO_2$ pipeline monitoring objectives:
    - "CCS" OR "CCUS" AND "pipeline" AND "monitoring";
    - "$CO_2$ pipeline" AND "monitoring" OR "instrumentation";
    - "$CO_2$ transport" AND "sensor network" or "sensor grid";
2. Optimization of pipeline monitoring:
    - "Sensor placement" AND "pipeline monitoring" AND "optimization";
    - "Leak detection" AND "pipeline" AND "optimization";
    - "Pipeline monitoring" AND "machine learning" OR "fault detection".

The identified literature sources were further shortlisted to focus on those publications that undertook the following:

- Proposed optimization methods related to pipeline monitoring;
- Addressed sensor placement for various monitoring objectives;

- Offered insights applicable to the pipeline networks.

Publications focusing purely on sensor hardware or capture/storage stages without pipeline transport relevance were not analyzed further.

As a result of the selection process, a total of 103 sources were identified and incorporated into this review. These sources were collected from a wide range of materials, including 61 peer-reviewed journal articles, 13 conference proceedings, and 10 technical reports, as well as handbooks, policy briefs, and monographs. The selection aimed to ensure a comprehensive coverage of both academic developments and industrial practices relevant to $CO_2$ pipeline monitoring and optimization.

The collected sources were analyzed based on their relevance to $CO_2$ pipeline monitoring, presence of modeling or optimization content, and potential applicability to real-world transport systems. Evaluation considered both technical depth and domain relevance, including analogous studies from non-$CO_2$ networks. The studies were grouped according to the key monitoring objectives (Section 3); classified by specific functions such as leak detection, flow measurement, and impurity monitoring (Section 4); and further assessed to inform optimization strategies (Section 5). Comparisons were made based on system type, monitoring goal, and method characteristics to identify transferable approaches and research gaps. However, almost no direct optimization studies on $CO_2$ pipeline monitoring were found. Section 5, therefore, incorporates relevant studies from other domains, selected as part of the initial screening process, to assess their relevance and adaptability to $CO_2$ pipeline conditions by considering the types of pipeline network topologies, monitoring needs, and operational conditions.

## 3. $CO_2$ Pipeline 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;
- Fiscal metering for commercial purposes (custody transfer).

The pipeline monitoring objectives address the detection and location of pipeline failure (including leaks and ruptures) and identify 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 flow rate, pressure and temperature, composition, and the amount of impurities and contaminants).

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., [18–23]).

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., [13,24]), or third-party damage (e.g., upon excavation, vandalism, or theft activity) (see, e.g., [25,26]). Undetected pipeline leaks may evolve into larger ruptures and bursts, leading to catastrophic consequences and fatalities (e.g., [27,28]). In the context of natural gas pipelines, hydrate formation is also recognized as a significant contributor to flow restriction and blockage, which in turn can induce abnormal pressure build-up and increase the risk of pipeline failure and leakage. As discussed by Qu et al. [29], hydrates may form and accumulate under high-pressure and low-temperature conditions, leading to operational incidents if not detected in time. This highlights the importance of integrating hydrate detection capabilities into leak detection and monitoring frameworks, particularly for multi-phase gas pipelines.

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 [30], although this has been noted as a statistical outcome rather than a reflection of intrinsic risk similarity, and no failure models were developed or used in deriving these estimates, which should be interpreted with caution due to different risk characteristics. Approximately 7% of accidents reported in the PHMSA database during the period from 2010 to 2017 were identified using computerized monitoring systems [31]. While $CO_2$ pipeline ruptures can happen (as in the recent accident near Satartia, Mississippi, USA [24]) and may have catastrophic consequences in case of pipelines passing through populated areas, they are comparatively less statistically frequent than ruptures in hydrocarbon pipelines [30]. At the same time, $CO_2$ pipelines are more prone to smaller size leaks than the hydrocarbon pipelines [32,33], highlighting the need for the leak detection and monitoring of $CO_2$ pipelines.

For pipeline systems in general, detecting and localizing pipeline leaks has attracted much attention, with a number of effective techniques and methods proposed in the past few decades [34–38], including Computational Pipeline Monitoring (CPM), which detects leaks by examining anomalies in the flow by comparing the real-time measurements of the flow with predictions made by a digital model [39]. Furthermore, leak detection and localization can be an integral part of the pipeline control and emergency shutdown system (see, e.g., [40–43]) aimed at mitigating the consequences of pipeline failure—minimizing the damage to the environment or escalation of safety hazards [44]. Supervisory Control And Data Acquisition (SCADA) system provides a platform for collecting in real-time the measurements of pressure, temperature, and flow rate 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., [16,39,45,46]).

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 [47]. However, more recently, integrating CPM systems with SCADA and Digital Twin (DT) technology, predicting the system's future states using the real-time measurements [48–51], has been proposed as a solution that can potentially improve the monitoring and operational integrity of $CO_2$ pipelines and networks [52–54].

Apart from leak detection and localization, control of potential operational threats in $CO_2$ pipelines requires careful monitoring of the flow conditions [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, shutdown, depressurization, and normal operation conditions may pose risks of pipeline overpressure and impact the water solubility in dense-phase $CO_2$;
- The temperature variations during start-up, shutdown, and normal operations may alter the $CO_2$ thermodynamic state, the density of $CO_2$ fluid, and the pipeline transportation capacity;

- Measurement of the flow rate and composition of $CO_2$ streams against the product specifications is important for custody transfer to ensure the quantity and quality of the $CO_2$ delivered by the pipeline operator.

The principles and methods of measuring flow rates in pipelines transporting gases and liquids are well established (see, e.g., [55]). However, adapting these methods to $CO_2$ pipelines faces a number of challenges, which are associated with the following:

(a) Unique physical properties of $CO_2$, e.g., the acoustic attenuation posing a challenge for using ultrasonic flow meters and the presence of impurities that can affect the thermodynamic properties and phase equilibria;
(b) Measurement uncertainties due to pressure or temperature variations in a pipeline system;
(c) The lack of standards and calibration facilities available for industrial use [53,56,57].

Although 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., [58,59]). 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 [60]. As pointed out by Chinello et al. [56], 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. While impurities like water, $SO_2$, or $H_2S$ are typically removed to meet transport specifications and reduce corrosion or safety risks, small amounts of inert gases such as nitrogen can actually help lower the risk of hydrate formation by shifting the phase boundaries (see, e.g., [61]). The location and design of purification facilities can also affect monitoring needs, but these aspects are beyond the scope of this review.

In summary, monitoring $CO_2$ pipelines involves several unique challenges not typically encountered in conventional pipeline systems. These include the following:

- Phase transition risks—due to the proximity of CO2 pipeline operation conditions to the $CO_2$ saturation line, two-phase flow can occur during start-up, shutdown, or depressurization;
- Impurities and corrosion hazards—trace components such as $H_2O$, $SO_2$, or $H_2S$ may cause corrosion or safety risks, requiring continuous composition monitoring;
- High measurement uncertainty—arising from compressibility effects, temperature sensitivity, and lack of standardized instrumentation;
- Dense-gas safety risks—as released $CO_2$ can accumulate in low-lying areas and pose asphyxiation hazards to humans;
- Transient flow conditions—driven by fluctuating capture and injection rates from industrial sources;
- Lack of standardized monitoring protocols—creating ambiguity in design requirements and performance expectations.

These features must be considered when adapting existing monitoring optimization methods to $CO_2$ transport. While this review does not address all the above challenges, Section 5 focuses on those most directly linked to leak detection, flow measurement, and composition monitoring.

# 4. Optimization of Pipeline Monitoring

As explained in Section 3, the pipeline monitoring systems serve various 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.

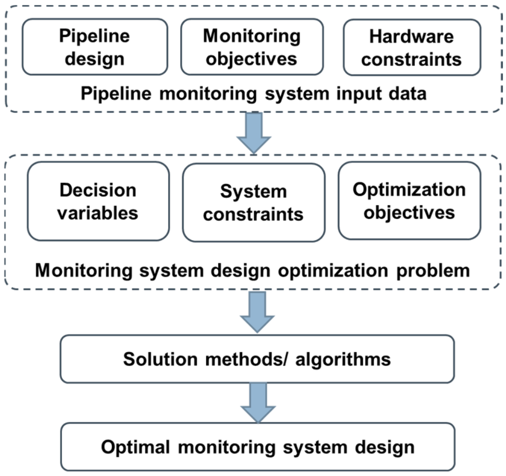


**Figure 2.** Methodology for pipeline monitoring systems design optimization.

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. [62]), 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 targeted literature review of the pipeline monitoring design optimization problems studied in the past in the context of the following:

(1) Leak detection and localization;
(2) Flow measurements;
(3) Fluid quality control;
(4) Improving energy efficiency and cost-effectiveness of the monitoring solutions.

## 4.1. 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 flow rate and using flow simulation techniques (e.g., CPM) to trace back these changes to the leak location [37,38]. The accuracy of the adopted technique depends on the spacing between the transducers, the uncertainty of pressure and flow rate measurements, and the level of noise/noise filtering algorithms adopted. As such, optimization of leak detection/localization 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. [63] 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) [64]. Similarly, Shiddiqi et al. [65] 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. The GA and its variations have become popular for solving non-linear sensor placement optimization problems [66]. Another sensor placement method, developed by Ribeiro et al. [67], involves optimizing the number of pipes to inspect and applying the TrustRank algorithm (see [68]) to refine the solution as part of a sensitivity analysis. Additionally, the Mixed-Integer Linear Programming (MILP) algorithm is frequently used for optimally placing sensors in pipeline systems. For instance, Xing et al. [69] studied the problem of sensor placement for robust burst (refers to sudden pipe rupture and break) event identification under sensor data uncertainties; the MILP method was applied to maximize the detection of the burst events under both limited and 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 save computational costs for flow simulations when optimizing the leak detection system performance [70–73].

For hydrocarbon pipeline transport systems, there are also various studies focusing on sensor placement for leak detection. For example, Zan et al. [74] 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 of 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. [75] employed the Adam-Mutated Genetic Algorithm (AMGA) to optimize sensor placement to detect ruptures subject to uncertainties of the simulation models. Sun et al. [76] accounted for the probability of leak scenarios 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 [77,78].

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 modeled and incorporated into the optimization process [69,74,75,79]. 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 [62,65,80] and long-distance oil transmission pipelines [81,82]. 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 [50,71,72].

### 4.2. 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 flow rates over a wide range of operating conditions, including possible multi-phase flow regimes, in pipelines transporting petroleum-derived liquids [83]. Specific challenges with flow rate 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 flow rates. 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 the low viscosity of the liquid for smooth operation and minimization of pipeline hydraulic losses. As such, in general, flow rate 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 flow rate measurements in pipelines. For example, Ferrari and Pizzo [84] developed a virtual flow meter for highly transient flows in pipelines transporting liquids. In another study, van Westering and Hellendoorn [85] 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.

### 4.3. 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 the measurement of composition and detection of contaminants in WDS. Preis et al. [86] 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. [87] 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. [88] 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 the NSGA-II algorithm [89] and applying the K-means clustering unsupervised ML algorithm [90] for Pareto front post-processing.

Composition tracking in gas pipeline transportation is equally important. For example, coupling the Gas Chromatography (GC) and the Optical Feedback Cavity-Enhanced Absorption Spectroscopy (OFCEAS) has been recommended as the optimal solution, balancing low costs and high accuracy, to meet the high purity requirements for hydrogen transport [91]. In the natural gas pipeline systems, computational transient flow models are used to resolve the state of flow and compositional variations across the network, e.g., [92–94]. However, there are no studies on optimizing impurity tracking at the monitoring system level.

### 4.4. 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. [82]. The optimization sought to maximize pipe coverage (i.e., the length of pipelines being monitored) and minimize the overall costs of the monitoring system. Varshney et al. [95] 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 [96] and Q-learning algorithms [97], were used by Rahmani et al. [98] 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.

## 5. Discussion: Recommendations on Optimizing the $CO_2$ Pipeline Monitoring Systems

As discussed at the end of Section 3, $CO_2$ pipeline monitoring presents several unique challenges that may require adapted or specialized optimization strategies. 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 4. The pipeline monitoring objectives that appear in the table can be grouped into three categories: (1) leak detection and localization; (2) measurement of the flow rate, pressure, and temperature; and (3) fluid quality and composition 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/non-linear, 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. For ease of reference, Table 1 maps the optimization approaches across different fluid systems. In this section, we draw from the map to explore which methods could be applicable or adaptable to $CO_2$ pipeline monitoring.

**Table 1.** Monitoring systems, optimization problems, and algorithms relevant to various pipeline transport systems.

| Transported Fluid and Network Type | Monitoring Objective(s) | Decision Variable(s) | Optimization Objective(s) | Type of Optimization Problem | Single/Multi-Objective | Method(s)/Algorithm(s) | Refs. |
|---|---|---|---|---|---|---|---|
| Water distribution networks | Loss quantification; leak localization | Hydraulic model parameters | Maximum accuracy of water loss detection and localization | Non-linear optimization problem | Single objective | GA | Wu and Sage [99] |
| | Leak localization | Sensor positions, leak/burst localization parameters | Maximum accuracy of leak localization | Non-linear optimization problem | Multi-objective | Data-driven, Multi-Objective Evolutionary Algorithm | Boatwright [100] |
| | | Positions of sensors | Minimum number of sensors; maximum accuracy of leak localization | Non-linear optimization problem | Single objective | ML classification and feature selection | Madbhavi et al. [72] |
| | Water quality and contamination detection and localization | Sensors positions | Minimum number of sensors, detection time, and population affected; maximum probability of detection | Non-linear optimization problem | Multi-objective | NSGA | He et al. [87], Cardoso et al. [88] |
| Urban drainage collection networks | Water quality and the presence of pathogens | Sensors positions | Minimum number of sensors; maximum network reliability and sensor node centrality | MILP or MINLP (depending on the problem formulation) | Single objective | SCIP algorithm (spatial branch-and-bound algorithm); Complex Network Theory | Simone et al. [101] |
| Oil transmission pipelines | Temperature and pressure monitoring | Sensor positions | Minimum power consumption by sensors | MILP | Single objective | Greedy algorithm | Guo et al. [78] |
| | Leak localization | Activity time of sensors | Minimum sensor's power consumption; maximum pipeline coverage | Non-linear optimization problem | Single objective | Reinforcement Learning Algorithm (AI Machine Learning) | Rahmani et al. [98] |
| 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. [50] |
| Natural gas distribution network | Estimating flow under uncertain demand | Sensors positions | Maximum accuracy of the measurement across entire network | Constrained MINLP | Single objective | Greedy algorithm (GA) | van Westering and Hellendoorn [85] |
| 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. [74] |

### *5.1. Leak Detection and Localization*

The experience in optimizing sensors for leak detection and localization in water distribution systems (WDS) 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 4.1. To be noted, WDS-inspired approaches offer useful structural insights, but applying them to $CO_2$ pipeline systems requires adjustment for differences in pressure regimes, compressibility, and monitoring objectives.

While there are no examples of optimizing monitoring systems for leak detection in $CO_2$ pipelines, recently, Kim et al. [62] applied Deep Learning methods to detect flow anomalies due to leaks and hydrate 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.

### *5.2. 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 [85], 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 relevant to placing flow rate measurement instruments in networks collecting fluctuating $CO_2$ sources.

Also, some studies focus on optimizing the accuracy of the flow rate measurements in pipelines. For example, as mentioned earlier in Section 4.2, Ferrari and Pizzo [84] developed a virtual flow meter to aid accurate estimation of mass flow rate 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. [62] applied Deep Learning to detect anomalies in the flow of dense-phase/supercritical $CO_2$ in a long pipeline caused by fluctuations in the 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, shutdown, 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 resolves the two-phase flow patterns.

### *5.3. Impurities Monitoring*

As can be seen in Table 1, sensor placement for the detection of contaminants has received significant attention in the context of monitoring of WDS (see, e.g., Cardoso et al. [88]). 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 are compatible 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, contaminant 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 [88] can be useful for facilitating the composition monitoring in $CO_2$ pipeline networks. Furthermore, as mentioned earlier, there are very few optimization studies specifically addressing composition tracking in gas pipelines. Although recently the composition tracking was discussed in the context of $CO_2$ pipelines [102], the proposed approach relies on using computational flow models to simulate the composition changes over time in the pipeline network, rather than on optimizing the monitoring system. However, this study opens a door to future research, making it possible to integrate these models into a comprehensive optimization framework for monitoring systems, as suggested in [92].

## 6. 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 the 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 structured literature review of the cutting-edge research on optimization of monitoring systems for leak detection and localization, flow metering, and fluid quality and component tracking in pipelines transporting various fluids, which can potentially be useful for $CO_2$ pipeline monitoring. The key findings and recommendations from this study can be summarized as follows:

- Sensor placement is the most studied pipeline monitoring optimization problem. Other optimization decision variables may include the types and combinations of sensors, as well as the optimal number of sensors or monitoring points;
- Methods of computer-based leak detection and localization, as well as optimal placement of monitoring sensors developed for pipelines transporting liquids (including water distribution systems and pipelines transporting crude oil and petroleum liquids), can be most 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 component tracking, such as those developed for water distribution systems, can be useful for enhancing the composition monitoring in $CO_2$ pipeline networks and potentially optimizing the composition monitoring systems. In addition, finding optimal combinations of measurement techniques, e.g., GC and OFCEAS instruments, as recently recommended for hydrogen transport, may further improve impurity measurement accuracy;
- $CO_2$ pipeline monitoring optimization can be described as a multi-objective optimization problem. While the accuracy of measurements, the number of sensors, and the 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 the multiple potential 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. For example, graph-based models or physics-informed neural networks (PINN) (see, e.g., [103]) may be promising for capturing both spatial correlations and underlying flow physics in $CO_2$ anomaly detection. This is particularly relevant for $CO_2$ pipelines, where flow dynamics are governed by known physical laws but data are often sparse and unevenly distributed. By embedding governing equations into the learning process, PINNs can leverage limited sensor data while ensuring consistency with the underlying physics.

**Author Contributions:** Conceptualization, methodology, and investigation, T.X. and S.M.; writing—original draft preparation, T.X.; writing—review and editing, T.X., S.M. and H.M.; visualization, S.M.; supervision, H.M.; project administration, H.M.; funding acquisition, H.M. and S.M. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement no. 101094664. The work reflects only the authors' views, and the European Union is not liable for any use that may be made of the information contained therein.

**Data Availability Statement:** No new data were created or analyzed in this study. Data sharing is not applicable to this article.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| AMGA | Adam-Mutated Genetic Algorithm |
| CCS | Carbon Capture and Storage |
| CPM | Computational Pipeline Monitoring |
| 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 |
| MINLP | Mixed-Integer Non-Linear Programming |
| ML | Machine Learning |
| MOEA | Multi-Objective Evolutionary Algorithm |
| PINN | Physics-Informed Neural Networks |
| PSO | Particle Swarm Optimization |
| RTC | Real-Time Control |
| SCADA | Supervisory Control and Data Acquisition |
| WDS | Water Distribution System |
| WSN | Wireless Sensor Network |

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