Improving the Resilience of Pipe Networks to Cold Spells using Machine Learning

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Summary

This research project explores the application of Q-learning, a form of reinforcement learning, to enhance the resilience of gas pipe networks during extreme cold events. By creating a simulated gas pipe network using the pandapipes framework, this study aims to dynamically suggest mitigation strategies to maintain or quickly restore gas pressure to safe operational levels. The approach leverages machine learning to predict and manage increased demand scenarios effectively, thus supporting the broader goals of enhancing infrastructure resilience and operational efficiency in the face of climate variability.

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Declaration

This project report is submitted towards an application for a degree in Mechanical Engineering at the University of Bristol. The report is based upon independent work by the candidate. All contributions from others have been acknowledged and the supervisor is identified on the front page. The views expressed within the report are those of the author and not of the University of Bristol.

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Contents

1 Introduction

1.1 Motivations

In the realm of natural gas distribution, it is essential to maintain optimal pressure levels throughout vast pipeline networks to ensure operational reliability and safety. Recent occurrences have emphasized the susceptibility of these networks to environmental stressors, especially cold spells that may significantly raise gas demand and disturb supply dynamics. The resilience of this infrastructure becomes a key issue for both utility companies and regulatory bodies as climate variability increases.

This study presents a new method of improving the resilience of gas pipeline systems during severe cold events using Q-learning, a type of reinforcement learning. This project seeks to simulate a gas pipeline network in Python using the pandapipes framework to model the dynamic responses of the network to increased demand and reduced capacity scenarios and implement strategic interventions that prevent critical pressure drops.

1.2 Aims and Objectives

The main aim of this research is to create a decision support tool that can dynamically recommend mitigation measures to sustain or rapidly restore the gas pressure at junctions to acceptable operational limits. The use of a Q-learning algorithm for the assessment of possible interventions, particularly the strategic placement of sources, is the focus of this research. The purpose of this tool is to improve the security of gas supply in peak demand and to increase the overall flexibility of the network to unforeseen disturbances.

Referencing the UK's 'National Emergency Plan: ‘Downstream Gas and Electricity’ highlights the importance of this project because of the possibility of gas supply disruptions in the UK that could lead to widespread energy emergencies [1]. This research is especially important as it aims at creating strong approaches to control such risks in the UK.

The methodology outlined in the subsequent sections involves developing a simulated gas pipe network, using the Q-learning model to learn and propose optimal strategies, and assessing these strategies through simulation. The findings seek to illustrate the capabilities of machine learning in enhancing the robustness of critical infrastructure systems to environmental and operational challenges, thus, contributing to the larger aim of strengthening infrastructure resilience and operational effectiveness in the context of growing climate variability.

2 Literature Review

This literature review explores current methods of improving gas network resilience, the impact of climate change on cold spells and how machine learning has the potential to close identified knowledge gaps in infrastructure resilience. This forms the foundation of the research by identifying the requirement of advanced tools to predict and manage the stresses resulting from cold spells on these crucial systems.

2.1 Pipe Network Resilience

The resilience of natural gas pipeline networks is critical, particularly considering that these systems are subject to different disturbances that can disrupt them completely. Stress resilience and recovery of these systems are the focus of research in this area, addressing innovative ways to improve robustness, especially under stress situations like conflicts or severe weather events.

A foundational study offers a thorough assessment of the resilience of natural gas pipeline systems, focusing on the requirement for strong operational models that can tolerate and recover from disruptions [2]. The research divides the methods into indicator construction, process analysis, and complex networks all of which help to understand how these systems can remain functional during disturbances.

Another important characteristic of network resilience is the capacity to manage congestion during disasters without sacrificing network throughput. This is illustrated by a study on Europe’s gas supply network, which is highly dependent on imports from geopolitically sensitive regions. The research produces a decentralized congestion management model, which is more robust due to the fact that it confines the effects of failures to local areas and minimizes reliance on centralized control [3].

Topological structure analysis is another method of assessing the robustness of pipeline networks. This approach evaluates the network's susceptibility to failures and suggests measures to improve its resilience by identifying critical nodes and links whose failure could disproportionately disrupt the network. This method is very important to learn how to manage risks that are caused by structural and operational deficiencies [4].

In combination, these studies emphasize the importance of advanced predictive and adaptive techniques in proper gas pipeline system management, particularly under adverse conditions. Knowledge in network management acquired during conflicts and other disasters has a lot of value since cold spells present an increasing threat as a result of global warming. The following section will delve deeper into the emerging problems arising from cold spells, thus confirming the need for the development of better management strategies that would help to forecast and reduce probable disturbances.

2.2 Cold Spells

Cold spells that are characterized by abrupt and dramatic fall in temperatures pose major challenges to the operation and management of natural gas pipeline networks. The cold spells' frequency and intensity are determined by larger climate changes that are important for proper infrastructure planning and management.

The IPCC's Sixth Assessment Report's chapter on 'Weather and Climate Extreme Events in a Changing Climate' provides a thorough scientific background, which emphasizes the rise in occurrence and intensity of extreme weather events, including cold spells, due to the global warming [5]. In addition, studies published in the Journal of Climate show that the loss of Arctic sea ice strongly weakens the stratospheric polar vortex, which may lead to more severe cold spells in temperate areas due to dynamic changes in atmospheric circulation [6]. These findings highlight the critical necessity for gas pipeline systems to change, focusing on the creation of predictive tools and approaches to deal with these highly dynamic conditions.

In combination, these sources illustrate the significance of blending modern climate science with gas pipeline network management approaches. They promote sophisticated machine learning models to predict and adjust to the growing stochasticity of cold spells. Such integration will ensure more robust pipeline systems and a guarantee of the system's reliability and safety even under unfavourable weather.

2.3 Machine Learning

Utilization of machine learning (ML) in gas pipeline systems has significantly enhanced the capabilities of monitoring, predicting and managing pipeline integrity and operational efficiency. This section outlines the recent applications and advances of ML in this field, showing its impact and potential.

Predictive Maintenance and Failure Modeling: The ability of machine learning to predict failures in gas transmission pipelines significantly enhances the safety and efficiency of pipeline operations. For example, one of the deep learning applications in failure modeling is the use of neural networks to predict pipeline failures in advance, leading to substantial benefits in proactive maintenance and risk management [7]. This is further illustrated by another study, which uses artificial intelligence for predicting failures, thus emphasizing the importance of machine learning in pipeline monitoring systems for real-time anomaly detection and failure prediction [8].

Dynamic Simulation and Operational Optimization: Machine learning is also important in dynamic modeling of gas pipeline networks. Methods that integrate interpretative machine learning models enable accurate modelling of pipeline performance, which is vital for operational decision support and strategic planning. These models enable the management and control of gas flows in real time across pipeline networks, guaranteeing operational efficiency and stability under different conditions [9].

Enhanced Liquid Handling Predictions: Studies on forecasting liquid loading in pipelines using machine learning offer solutions on how to deal with the problem of liquid accumulation, which can greatly affect the efficiency of gas transmission. Machine learning models provide more efficient prediction tools in predicting liquid loading events which allows for the development of improved management strategies to reduce the potential impact on pipeline functionality [10].

Accident Consequence Assessment and Safety Enhancements: Finally, machine learning helps to evaluate the impacts of pipeline accidents, particularly in urban areas. Through the simulation of different accident scenarios, these models allow pipeline operators to know the possible effects and develop appropriate mitigation strategies, in turn, improving safety measures and reducing the risks related to pipeline operations [11].

The incorporation of machine learning into gas pipeline management has created new opportunities to improve safety, efficiency and reliability of these important infrastructures. With the development of the technology, the further improvement of ML models should be the main driver of significant innovations in the field.

2.4 Gaps and Opportunities for Research

Though many advances have been made in the use of machine learning (ML) in gas pipeline management, there are still some major gaps especially with regards to the use of unsupervised and reinforcement learning techniques. Such spaces offer great opportunities for innovative research that can significantly improve the effectiveness, safety, and stability of pipeline operations.

Unexplored Territory in Machine Learning: Most of the current literature concentrates on supervised learning models for predictive maintenance and detection of anomalies in gas pipelines. Nevertheless, the studies that utilise unsupervised learning are quite scarce, which could uncover new patterns and anomalies without pre-labelling of data. This is a critical research gap, which indicates a possibility of creating models that could automatically discover and learn from new data, improving the predictive abilities of the current systems.

Reinforcement Learning for Dynamic Optimization: The utilization of reinforcement learning (RL), specifically Q-learning, presents a significant but underutilized opportunity in operational management of pipelines. In dynamic decision-making processes, Q-learning is unique in its transformative power which allows systems to adjust and learn the best operational strategies from real-time data. The article “Machine Learning in Energy Conversion and Management” demonstrates the importance of Q-learning in the optimization of energy systems in dealing with complex dynamic operational issues efficiently [12]. This is reinforced by a study from “Optimal Scheduling of Island Integrated Energy Systems”, which shows that Q-learning is effective in addressing the uncertainties of energy system management, such as those encountered by gas pipelines during cold spells [13]. In addition, the paper “Reinforcement Learning in Optimizing Energy Systems” emphasizes on the versatility of Q-learning, demonstrating its role in improving system resilience and operational efficiency, especially in harsh conditions [14]. Altogether, these studies demonstrate that the incorporation of Q-learning is not only possible but also advantageous in gas pipeline simulations, improving performance and resilience considerably and providing a strong basis for tactical real-time adjustments and operational optimization.

Cross-Disciplinary Approaches: By integrating knowledge from other related fields, for instance, telecommunications and aerospace, where unsupervised and reinforcement learning have been more widely used, new approaches and methods for controlling complicated pipeline networks could be developed. Such interdisciplinary approaches would reveal creative solutions for the long-term problems of pipeline management, especially in adapting to unforeseen changes and emergency management.

The proposed research seeks to fill these gaps and in doing so, it will improve the current state of the art in gas pipeline management and lay a foundation for future studies that would delve deeper into the machine learning potential in this critical infrastructure domain. This study may result in revolutionary progress in gas pipelines monitoring, maintenance, and optimization, thus enhancing the strength and reliability of the energy systems.

3 Methodology

In this study, a simulation-based approach has been used to evaluate the resilience of urban gas networks in cold spells. A digital twin model is used to dynamically replicate network behaviors and apply machine learning techniques. In particular, a Q-learning model allows for the determination and testing of best practices that improve network performance and reliability in environmental stress situations. This holistic approach enables the thorough investigation of how state-of-the-art machine learning methods can be easily incorporated into infrastructure management for the successful solution of practical problems. In addition, the flowchart (Fig. 1) given below provides a graphic representation of the whole process. The color coding helps in differentiating between the various stages of the methodology, thus making the structure and sequence of tasks clearly visible.

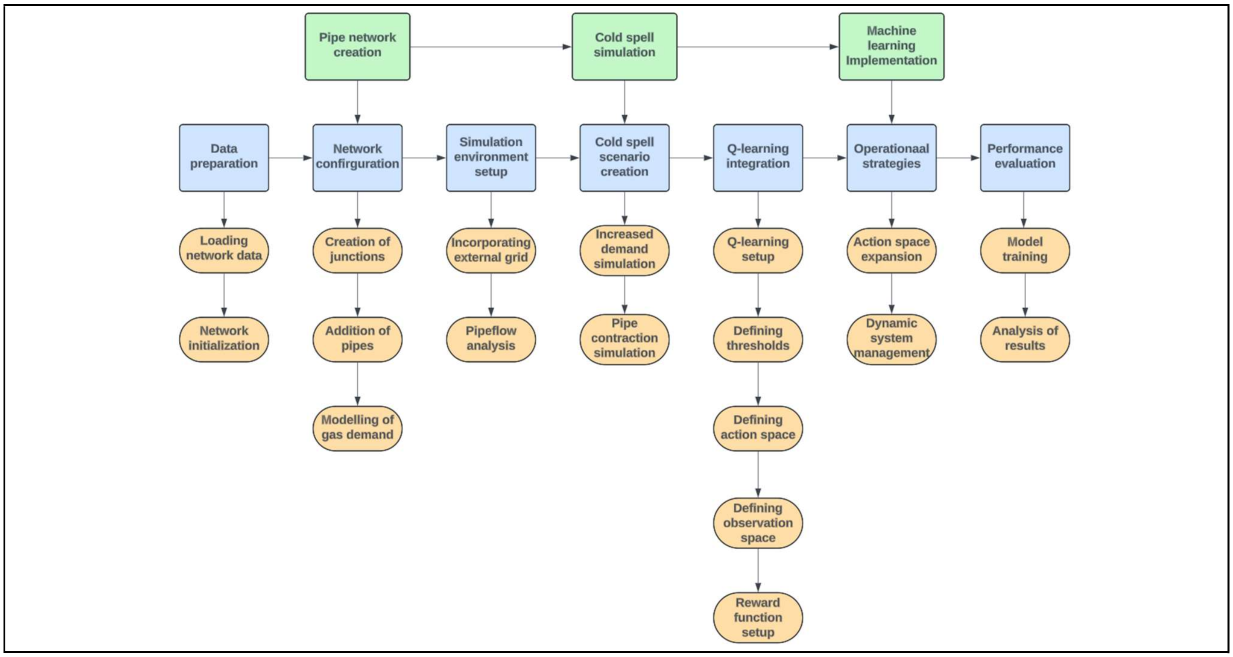

Fig 1. Detailed flow chart of the methodology showing: Mains sections as green boxes, Sub-sections as blue boxes and the specific tasks performed within the subsections as yellow boxes.

3.1 Pipe Network Creation

3.1.1 Data Preparation

This section outlines the creation of a virtual gas network, which was created in Python using the PyCharm Integrated Development Environment (IDE). The complexity of the project resulted in the development of a class called "GasPipeNetworkSimulation" which is built on the pandapipes framework. This class is utilized in order to organize simulation tasks and integrate machine learning. Python's class-based setup is an adaptive approach that is appropriate for more advanced data processing and analysis in network simulations.

Loading Network Data

Importing the network data was the first step in the simulation process, which was the base of the model. The CSV format gave information on several network components such as pipe specifications, node locations, consumption rates, and pressure settings, which allowed for detailed and individual analysis. All imported data was converted to units compatible with the Pandapipes framework in order to obtain accurate results.

Pandas library of Python was used for thorough data manipulation and analysis of these CSV files converting them into structured data frames. This stage was critical in the data preparation for thorough analysis and manipulation, making sure that each data set was well interpreted for the required needs of the simulation framework. This careful treatment of the data is essential, providing the fidelity of the simulation and its capability to accurately simulate real-world operating environments.

Network Initialization

After importing the required data, network initialization was the next step in the simulation. An empty network was established, which paved the way for the addition of pipes, junctions, and other elements. At this point, it is important to specify the working fluid that should simulate the behavior of gas under the normal operating conditions.

A sample network diagram (Fig. 2(a)) shows the basic structure applied in Pandapipes [15]. This diagram is accompanied by a legend (Fig. 2(b)), with definitions of all symbols like junctions (mass flow = 0), external grids, sources, sinks, pumps, pipes, and connections [16]. This visual presentation helps to comprehend the structure of the network and the gas flow in the system. It acts as a simple guide that highlights the general layout and elements found in a simulation.

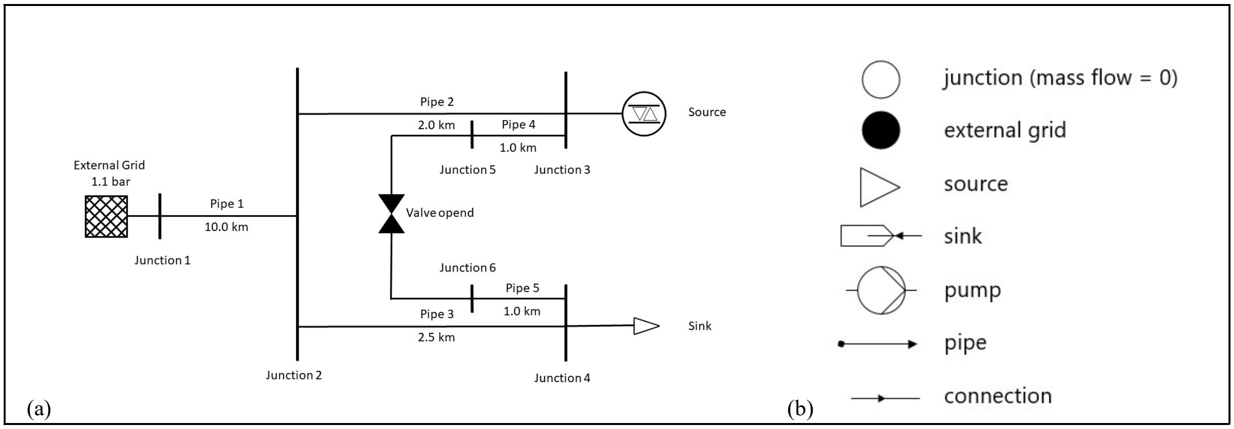

Fig 2. Gas network diagram showing: (a) Example pipe network layout (b) Legend of pipe network components.

3.1.2 Network Configuration

Creation of Junctions

Development of the simulated gas network begins with the introduction of junctions that serve as key points in the control of the flow and distribution of gas. These junctions are created based on geospatial data taken from CSV files, which represent the latitudinal and longitudinal positions of the nodes in the network.

To illustrate the functionality of junctions within the network, two figures from the Pandapipes documentation are included [17]:

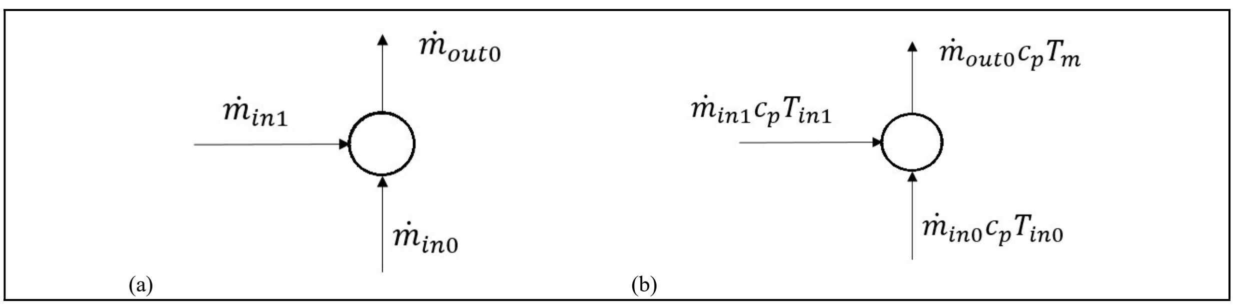

Fig 3. (a) Mass conservation at junction (b) Energy conservation at junction

Figure 3(a) provides a visual representation of a junction, detailing the mass flow entering and exiting. The mass conservation principle at a junction is depicted by equation 1 below:

$$\sum_{n=0}^{N} \dot{m}_{in_n} - \sum_{l=0}^{M} \dot{m}_{out_l} = 0 \qquad [1]$$

Where $\dot{m}_{in_n}$ represents the mass flow rate at the n^{th} inlet, $\dot{m}_{out_l}$ is the total mass flow rate at the l^{th} outlet, N is the number of inputs and M is the number of outputs.

This equation ensures the mass flow into the junction is equal to the mass flow out, maintaining mass balance essential for the simulation's realism [17].

Figure 3(b) corresponds to the conservation of energy at the junctions. This energy flow is governed by equation 2 below:

$$\sum_{n=0}^{N} \dot{m}_{in_n} c_p T_{in_n} - \sum_{l=0}^{M} \dot{m}_{out_l} c_p T_m = 0 \qquad [2]$$

Where c_p is the specific heat capacity of the fluid at constant pressure, T_{in_n} is the temperature of the fluid at the n^{th} inlet and T_m is the mixed or average temperature of the fluid exiting the junction.

This equation maintains the energy balance by taking into account the enthalpy of incoming and outgoing gas flows so that energy is conserved in the network [17].

These figures, together with the equations upon which they are based, are essential for the comprehension of how the simulation guarantees the maintenance of the continuity and energy conservation laws at the junctions. They give the computational rules that Pandapipes uses to compute the different network states under different operating conditions.

Addition of Pipes

The simulation continued with the incorporation of pipes, which serve as the channels of gas movement in the network. Each pipe's parameters were defined to reflect the real-world characteristics of the network. In accordance with the principles of fluid dynamics for incompressible media, equation 3 is utilized to calculate pressure loss (p_{loss}) across the pipes [18]:

$$p_{loss} = \rho \cdot g \cdot \Delta h - \frac{\rho \cdot \lambda(v) \cdot l \cdot v^2}{2 \cdot d} - \zeta \cdot \frac{\rho \cdot v^2}{2} \qquad [3]$$

Where p_{loss} is the pressure loss, ρ is the density, g is the gravitational acceleration, Δh is the change in elevation between start and end point of pipe, $\lambda(v)$ is the darcy friction factor, l is the length of the pipe, v is the velocity of the fluid flow, d is the diameter of the pipe and ζ is the sum of minor losses.

For turbulent flow conditions often encountered in gas pipelines, the Nikuradse model provides the friction factor (λ) through equation 4 below [18]:

$$\lambda = \frac{64}{Re} + \frac{1}{\left(-2 \cdot \log \frac{k}{3.71 \cdot d}\right)^2} \qquad [4]$$

Where Re is the Reynold's number, k is the pipe's roughness coefficient and d is the pipe diameter.

This equation was chosen based on the assumption of incompressible flow, which is a valid approximation for the natural gas within the operating velocities of typical urban gas networks. The friction model parameters are in line with the Nikuradse model, which is set as the default in Pandapipes and is widely accepted for this kind of engineering analysis.

An illustrative diagram from the pandapipes documentation (Fig. 4) shows a section of pipe with designated pressure points (P_{from} and P_{to}) and the pressure drop (dP_{loss}) that occurs along its length [18].

Fig 4. Pipe model showing the flow and pressure drop from origin to destination.

Modeling Gas Demand

Once pipes are added, the next step is to model gas consumption at each node using "sinks", a pandapipes feature. The consumption rates should be transformed to units that are compatible with the simulation environment, which is usually cubic meters per second (m^3/s), using a suitable conversion factor. This guarantees that the simulated requirements are consistent with the demands that the framework needs for the correct hydraulic analysis.

The concept of a "sink" in pandapipes refers to the place where gas is extracted from the pipeline network, with the magnitude of mass flow being directly proportional to the amount leaving the network [19]. This configuration is essential for emulating real load conditions in the network and practicing scenario-based testing.

The demand increase method to simulate cold spell conditions is fundamental to this research and will be described in the 'Cold Spell Scenario creation' section of the methodology. In this regard, the sink parameters will be adjusted to reflect the expected increase in gas demand during winter. This model is critical in assessing the network's capability to sustain service levels during peak demand.

3.1.3 Simulation Environment Setup

Incorporating an External Grid

Upon modelling gas demand, the simulation called for an external grid to be introduced for maintenance of stable operation. The external grid was key in defining nodes with predetermined pressure values, unlike a standard source component that introduces a fixed flow rate. The reason for this choice was the requirement for a pressure point of reference with infinite capacity that would solve convergence problems usually met in complex network simulations.

The pandapipes documentation defines an external grid as a node that has fixed pressures or temperatures, which are not variables to be solved in the simulation [20]. Usually, an external grid represents a node's relation to a larger system, for example, a main supply line that supplies a localized network. An external grid allowed the simulation to correctly represent the effect of a high-capacity pressure source on the network without having to pre-determine mass flow rates, which are instead derived from the pipe flow analysis. This strategic inclusion was a critical factor for a successful simulation that set the stage for many other scenarios, such as those that simulate the influence of cold spells on network pressure and flow dynamics.

Defining Thresholds and Objectives

In the method for modeling the resilience of gas pipeline networks, setting proper operational thresholds is crucial. The range of the acceptable pressure is established in accordance with usual practices of the industry where considerable pressure fluctuations are typical. For a conservative yet realistic simulation, pressures within the network are maintained within a specified percentage of the reference pressure, using equation 5 below:

$$Minimum\ pressure\ \geq Threshold \qquad [5]$$

This approach ensures network stability and safety during simulations, reflecting the precision needed in actual pipeline management to maintain system integrity and responsiveness to environmental changes.

Pipe Flow Analysis

The last step in the development of the gas network was to start the pipe flow analysis using the "pipeflow" function in pandapipes. This function is the heart of the simulation, using the Newton-Raphson method to solve the nonlinear system of equations that describes the gas flow in the network in an iterative manner.

The Newton-Raphson solver is a numerical method selected for its reliability and effectiveness in addressing intricate networks with numerous nodes and interconnections. It uses an approximation of the system's Jacobian matrix and solves for pressure and flow rates which satisfy the mass and energy conservation laws throughout the network [21]. The accuracy and convergence of the solver are critical for the network's simulated behaviors to be a correct representation of the actual operations.

The "simple_plot" function was employed to produce a plot of the entire network layout for visualization purposes (Fig. 5). The schematic represents the network's structure in a clear manner, showing the different components including pipes, junctions, sinks, and the external grid. The graphical representation is a useful tool in both validating the network's configuration and communicating the simulation's size and complexity.

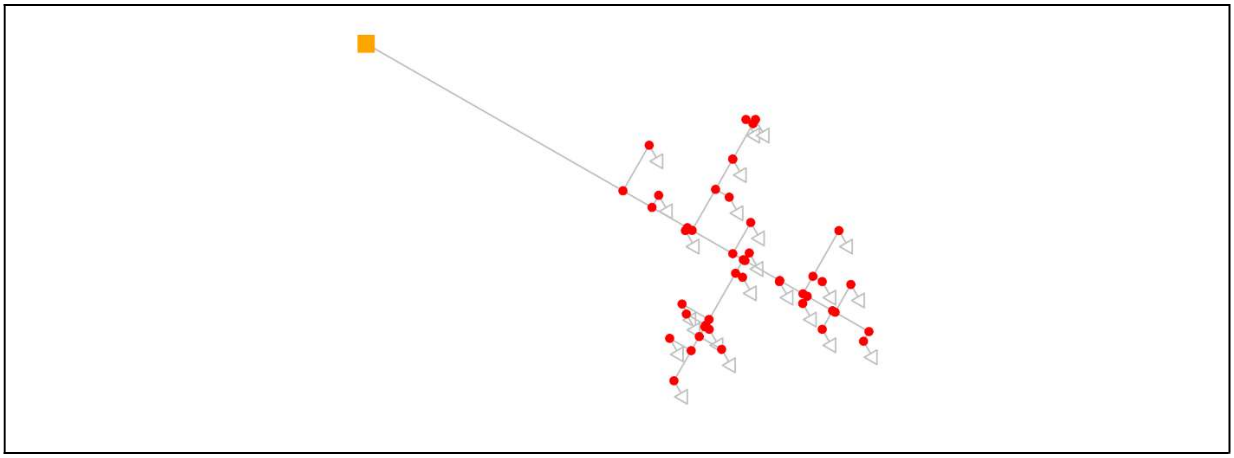

Fig.5 Simulated pipe network: with junctions as red dots, sinks as arrows and the external grid as a yellow square.

This implementation stage is very important because it integrates all the components of the network model, making it possible to perform dynamic analysis of the system under different conditions. It is the starting point of the transition from the static network design to active simulation which paves the way for subsequent sections that discuss particular scenarios like cold spell simulations and application of machine learning approaches for improved predictive abilities.

3.2 Cold Spell Simulation

This section emphasizes the resistance of gas networks to cold spells intensified by global warming. It evaluates test cases that simulate threats like surge in demand and potential freezing of the system, checking the network's capability to withstand such conditions and identifying weak points. The knowledge gained from these simulations is used to integrate machine learning solutions in order to enhance network resilience. The remaining paragraphs will consider methods used to reproduce these states and will provide a more detailed study of network behavior during cold spells.

3.2.1 Cold Spell Scenario Creation

Increased Demand Simulation

In the cold spell scenario simulation, household gas demand increases are modeled to reflect typical usage spikes during colder months. This is achieved through the application of a 'demand increase factor' (DIF), calculated using equation 6 below:

$$Cold\ spell\ demand = Baseline\ consumption\ rate \cdot DIF \qquad [6]$$

This way every node that is a sink in the network will get a moderate rise in gas consumption. The model visits all nodes and distributes the DIF equally, allowing us to observe the performance of the network under an increased demand.

In addition, this approach introduces random variability to demand increases by sampling the DIF from a normal distribution, thus, a standard deviation is introduced. This approach imitates the natural diversity of gas consumption in households and enables to model the impact of a range of cold spells on the system, which guarantees the accuracy of the findings. The dynamic variability of the network simulation allows it to be used in various situations in which the robustness and efficiency of machine learning approaches in maintaining operational stability are evaluated.

Pipe Contraction Simulation

This portion of the methodology focuses on replicating the physical effects of freezing temperatures on gas pipelines, a critical factor during cold spells. The method utilized involves adjusting the physical parameters of the pipes to mimic freezing conditions effectively. This is modeled using a 'reduction factor' (RF), where the cold spell diameter is calculated using equation 7 below:

$$Cold\ spell\ diameter = Baseline\ diameter \cdot RF \qquad [7]$$

This factor is determined based on general guidelines to simulate realistic contractions in diameter due to low temperatures. The RF is applied variably across the network using a normal distribution to introduce realistic variability, enhancing the simulation's accuracy and applicability to diverse scenarios.

3.3 Machine Learning Implementation

This part of the methodology presents the incorporation of Q-learning into our simulation framework to improve decision-making in gas network management during cold spells. This method enables the system to learn and adapt the most effective operational strategies incrementally, thus improving the resilience and efficiency of the network. The next sections will detail the systematic procedures of integrating Q-learning into the simulation, showing how it interacts with the network model to enhance performance and resilience through continuous feedback and adaption.

3.3.1 Q-learning Integration

Setting up the Q-learning Framework

The incorporation of the Q-learning framework into the simulation is critical for improving the decision-making capacity during cold spell conditions. In order to effectively integrate Q-learning into the simulation, a specialized Q-learning class was developed using Python. This class is the core of the learning mechanism which enables the system to systematically assess and improve strategies through iterative simulations.

Q-learning is selected for its success in such environments and uses the Bellman equation aiming at the best possible balance between the immediate and future rewards [22]. This equation expresses the connection between present actions and future gains. This expression can be seen in equation 8 below:

$$Q(s,a) = r(s,a) + \gamma \underbrace{max}_{a} Q(s',a) \qquad [8]$$

Where Q (s, a) is the Q value yielded at state 's' and selected action 'a', r(s, a) is the immediate reward received, $\gamma maxQ(s',a)$ is the best Q value from state 's' and γ is the discount factor that determine the importance of the current state.

This equation modifies the knowledge of the agent, which is captured in a Q-table that reflects the expected value of actions in states. The Q-table (Fig. 6) itself is in the form of a grid with states as rows and actions as columns. A graphical representation of this is shown in figure 6 below [23].

Actions

States

	A_1	A_2	...	A_M
S_1	$Q(S_1, A_1)$	$Q(S_1, A_2)$		$Q(S_1, A_M)$
S_2	$Q(S_2, A_1)$	$Q(S_2, A_2)$		$Q(S_2, A_M)$
$\vdots$			$\ddots$	$\vdots$
S_N	$Q(S_N, A_1)$	$Q(S_N, A_2)$	...	$Q(S_N, A_M)$

Fig. 6 Example Q-table: Displays Q-values representing the expected utility for actions (columns) across different states (rows) in a Q-learning model.

Moreover, the epsilon-greedy strategy ensures a calculated approach to action selection, balancing between exploration and exploitation. This method is pivotal for efficiently navigating the trade-off between learning new strategies and leveraging the most rewarding known strategies, fundamental in reinforcement learning [24]. This is visually demonstrated by the following decision-making diagram (Fig. 7) [23].

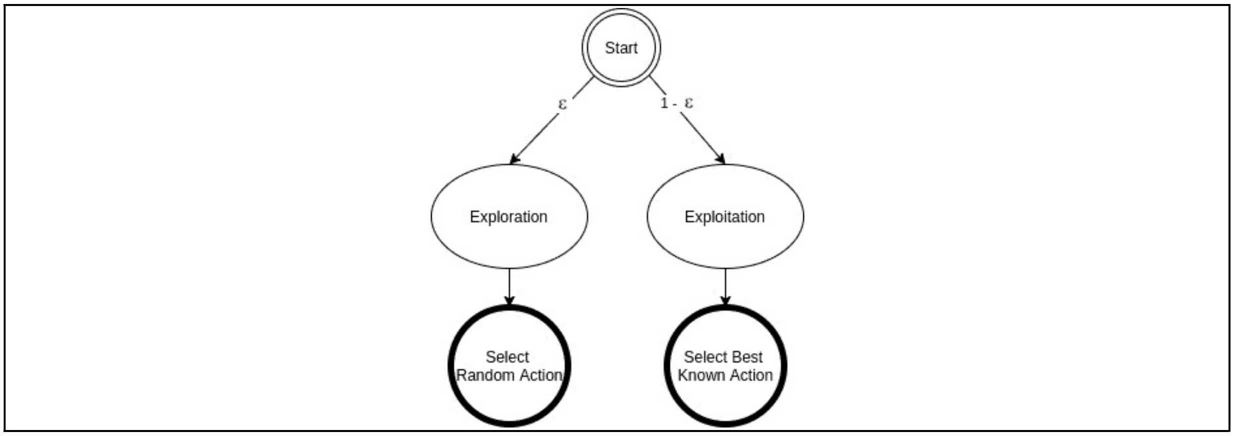

Fig. 7 Epsilon greedy strategy decision diagram

To accommodate the learning process, the Q-learning agent was programmed with a distinct set of parameters:

- Learning Rate (α): Governing the pace at which new information updates the Q-values, reflecting on the agility of the agent's learning.
- Discount Factor (γ): Influencing the weighting of future rewards, it dictates the foresight in strategic thinking.
- Exploration Rate (ε): Decides the rate at which the agent explores new strategies and exploits best known actions.

These parameters were fine-tuned to ensure an effective learning curve, allowing the agent to adapt its strategy incrementally.

Ultimately, the Q-table is updated through an iterative process based on the observed outcomes of actions taken. The update rule, essential for reinforcing successful strategies, is formulated using equation 9 below:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \underbrace{max}_{a} Q(S_{t+1}, a) - Q(S_t, A_t) \right] \qquad [9]$$

Where S_t is the current state of the agent at time t, A_t is the action taken by the agent at time t, α is the learning rate, γ is the discount factor, S_{t+1} is the state of the agent at time t+1 and R_{t+1} is the reward received after moving to state S_{t+1}.

In this study, the first Q-learning model used a single action to set the baseline performance. Complexity of the model was increased by enlarging the action space, allowing the agent to identify and implement a more refined strategy within the simulated gas network.

By incorporating the Q-learning framework, we enable the improvement of the network's operational efficiency, especially under cold spell conditions. The methodologies presented here detail the systematic development of an intelligent system that can learn and adapt for system resilience.

Integration and Expansion of the Action Space

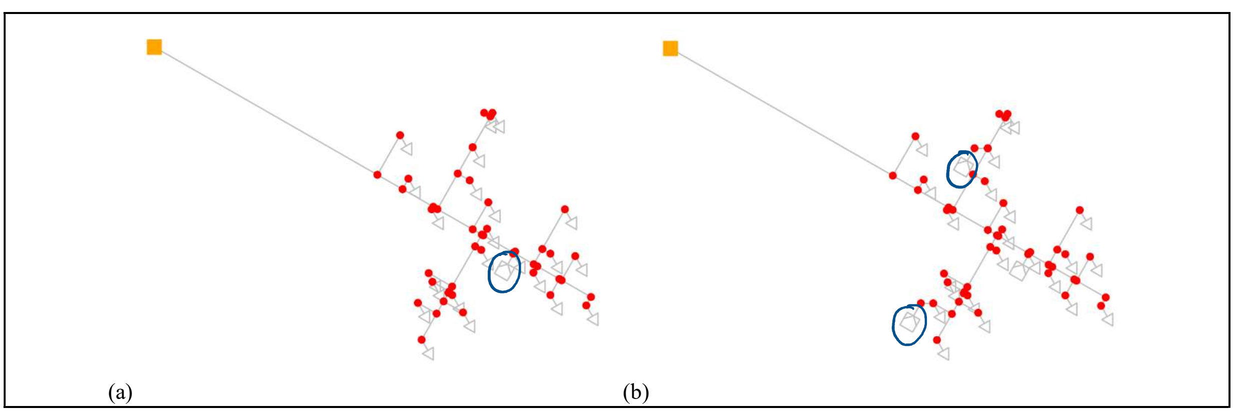

Fig.8 (a) Initial source addition to network (b) Additional source locations post action space expansion.

The actions that could be taken by the Q-learning agent were defined prior to simulation. At first, the addition of a strategic source to increase network pressure was included as the main action. This basic action is depicted in Fig. 8(a), that shows how strategic interventions can affect network dynamics. The visualization helps to understand the practical consequences of Q-learning decisions and to anchor the abstract concepts in the concrete framework of the network model.

In order to improve the strategic decision-making capacity within the gas network simulation, the action space was broadened to incorporate multiple strategic source locations. This extension permits testing of different configurations throughout the network, monitoring their impact on pressure distribution and optimization of responses under various cold spell scenarios. The addition of extra strategic source locations, each in different levels of congestion with different flow rates, allows the system to identify and implement the best strategies to maintain optimal pressure levels throughout the network. This expanded action space is represented in Fig. 8(b), that shows the position of all three sources and emphasizes the coverage they offer.

Observation Space Configuration

A Discretized state space was utilized in the simulation to form the observation space in Q-learning. Initially, although the pressure range was intended to be considered as continuous across junctions an operational decision was taken to concentrate on the lowest pressure within the network. The simplifying strategy made each state represent only one pressure value; hence, it allowed the association of each state with its corresponding actions. Concentrating on the minimum pressure within the distribution system was critical since it allowed interventions to be targeted at the most vital pressure points, ensuring operational standards with minimal effort. The method "get state" was created to compute the minimum pressure over all junctions, thus converting the continuous measure into a discrete index that is appropriate for the processing demands of Q-learning.

Designing the Reward Function and Check if Done Criteria

The reward function is a key element in the Q-learning implementation for the gas network simulation. The reward system functionality is depicted in a flowchart (Fig. 9), aiming to promote actions that push network pressure towards a defined threshold. This chart specifies the situations in which rewards or penalties are given, based on the pressure of the network with respect to the desired threshold. This approach not only makes understanding easy but also shows the practical application of the reward mechanism in effective network dynamics control.

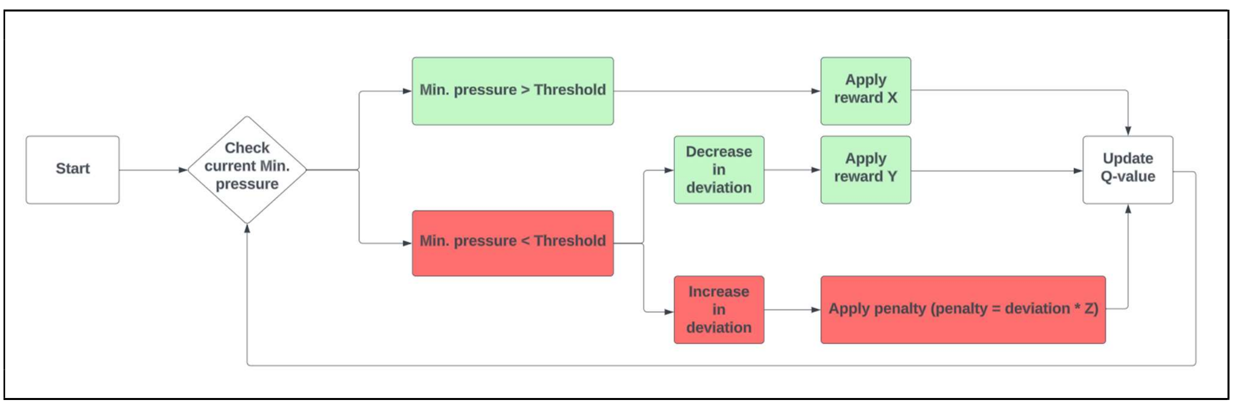

Fig. 9 Reward function mechanism flowchart

The flowchart presentation of the implementation of the reward system application illustrates that tactical modifications in network operations can bring about improvement. This abstract method is flexible which makes it suitable for different contexts and network conditions. The systematic approach is critical in making it clear how small changes in the operational strategies can significantly improve the recoverability and efficiency of gas network systems in different situations.

The "check_if_done" function plays crucial role in the methodology of the simulation, which defines the end of the simulation. It stops the learning process when the minimum pressure of the network stabilizes within a certain percentage of a predetermined reference pressure that exemplifies optimal operational conditions.

Setting this function guarantees that network performance remains within the specified threshold pressure for stability and thus, ensures desired operational efficiency and performance.

3.3.2 Operational Strategies

Dynamic System Management

One of the key components of the methodology aimed at enhancing the cold weather resilience of the urban gas network is the dynamic system management (DSM). The DSM is organized according to the "step" method that is necessary for the dynamic adaptations in the action domain specified.

The step method is responsible for carrying out actions within the network. The actions are performed in order to dynamically control network loading. The analysis of the present network state starts with the minimum pressure analysis at all junctions to detect the need for immediate modifications.

The simulation environment is updated each time an action is executed, thus providing a real-time performance feedback on the strategies used. This approach allows to see and to assess the real impact of strategic interventions on the network dynamics. The results of these actions have a direct impact on the learning process of the Q-learning algorithm and improve the accuracy of decision making during the following simulation episodes.

Additionally, the step approach consists of reward evaluations that support the adaptive learning process. Each action is tested on how it is able to modulate the pressure profile of the network and rewards or penalties are then determined. These estimates are very important for the learning of the Q-learning model on the best strategies in different situations. This method incorporates the reward functions discussed before, so that the actions leading to the optimal pressure levels are rewarded and less effective actions are penalized.

The method returns the new state of the network and the reward of the action taken, thereby, providing the required feedback loop for the iterative learning and adaptation of the system. This live feedback technique gives the system the ability to make instant changes to its operation scheme that provides strategic planning required to boost the resilience to negative impacts.

DSM provides the unity of an action space and reward functions, allowing the network to adapt dynamically to real-time conditions and supports immediate operational changes. This integration guarantees the resilience and strategic management of the gas network infrastructure, thus showing the success of the integrated machine learning techniques in the critical infrastructure management.

3.3.3 Performance Evaluation

Model Training and Analysis of Results

The training of the Q-learning model is achieved through iterative simulations that gradually improve the decision-making ability of the Q-learning agent. Initially, the model parameters which include the learning rate (α), discount factor (λ), and exploration rate (ε) are determined. These parameters determine the integration of new information, the discount factor for future rewards, and the exploration/exploitation balance.

In this process of training, the number of steps and simulations increases gradually, making the agent exposed to many more scenarios, which help in its generalization and decision making across different network conditions. Every simulation episode begins with the network at its initial state and proceeds through a set of agent actions.

Action selection and execution is carried out through the step function, which gives feedback by modifying the Q-table with the new state and reward. The table keeps the value of each action in each state which helps the agent to make decisions. Parameters such as epsilon are adaptively updated to reduce exploration in favor of exploiting learned strategies as the agent's certainty increases. The adaptive approach reduces the likelihood of making incorrect decisions and thus guarantees strength of the training.

Such iterative training and constant improvement of model parameters help the Q-learning agent to learn the correct actions and maintain the network stability and efficiency in a variety of conditions, which is in line with dynamic requirements of management of urban gas networks during severe winter cold.

4 Case Study

The approach of this research is based on the detailed case study of the gas network of Austin, Texas, obtained from a numerical model supplied from the Texas A&M Engineering Experiment Station (Travis 150 system) [25]. Although the synthetic model is simulated using hypothetical data, it closely copies the operational dynamics and infrastructure layout of actual urban gas networks and as such provides a perfect platform for simulation and analysis.

Only the gas network part of the Travis 150 System was considered for purposes of this research. The model consists of specific data concerning the topology of the network, node coordinates and pipeline configurations. These components are essential in accurately modeling the network's response to different operational states and in testing the efficacy of machine learning interventions. The specific parameters that have been used for the simulation are provided in the accompanying table (Tab. 1).

Tab. 1 Case study specific parameters used for simulation along with their values and reasons for their use.

Parameter	Value/range	Description and justification
Gas	N/A	For the correct implementation of the gas properties in the pipeline network, the working fluid was given as 'lgas'. This specification of the fluid is one of the predefined fluids in pandapipes which represents typical behavior of natural gas under normal operational conditions [26].
Consumption data	N/A	The consumption data, initially measured in millions of cubic feet per month (MMCF/mo), was converted to cubic meters per second (m^3/s) to fit the simulation environment's unit system.
Demand increase factor	1.4 (mean), 0.1 (standard deviation)	The winter of 2022 recorded an average natural gas consumption of 122.4 Bcfd (billion cubic feet per day) [27], which is a marked rise from the annual average of 88.5 Bcfd [28]. In response, a demand increase factor of 1.4, indicating a 40% uptick in winter usage, was applied to the network's simulation. This factor was applied as the mean in a normal distribution with a standard deviation of 0.1 to introduce controlled variance into the simulation without overly complicating the model training.
Reduction factor	0.8 (mean), 0.1 (standard deviation)	Although specific data on diameter reduction due to cold spells is scarce, a conservative approach was adopted to evaluate the network's resilience. A reduction factor of 0.8 was chosen, representing a hypothetical 20% decrease in diameter, which is a plausible scenario during severe cold conditions. This factor was applied with a standard deviation of 0.1 to simulate realistic operational challenges, providing a controlled yet meaningful variation in network performance analysis.
Pressure range	10%	Based on industry insights, such as those discussed in PetroWiki, pressure fluctuations in pipeline systems can reach up to 20% [29]. To ensure a rigorous assessment of network resilience, the simulation adopts a stricter threshold, setting the acceptable pressure range at within 10% of the reference pressure set by the external grid.
Alpha (α)	0.1	In the Q-learning framework utilized for the case study, an alpha value of 0.1 was selected. This learning rate was determined to effectively balance the integration of new information with the retention of prior data. By setting alpha at 0.1, each update to the Q-table moderately adjusts the existing Q-values, mitigating the impact of high variability in rewards and promoting stable convergence towards the optimal policy over time. This setting ensures a steady progression in learning, incorporating new experiences while preventing drastic fluctuations in value estimation.
Discount factor (γ)	0.9	A gamma value of 0.9 was selected for the Q-learning parameters to effectively balance immediate and future rewards. This value ensures that the model prioritizes long-term stability alongside short-term gains, which is crucial for maintaining network resilience and efficiency during fluctuating demand in cold spells. This setting enhances strategic decision-making, focusing on sustained operational success in managing gas network pressures.
Exploration rate (ε)	0.9	An initial epsilon value of 0.9 was chosen, with a gradual decay over episodes. This high starting value promotes exploration of the action space early in the training, allowing the Q-learning model to discover diverse strategies. As episodes progress and the model gains experience, the epsilon value decays, shifting the focus towards exploiting known, effective strategies. This approach ensures a balanced exploration-exploitation trade-off, crucial for optimizing network management under varying conditions during cold spells.

The Austin networks complexity and realism make it an ideal testbed to train the Q-learning model. The model is able to provide a detailed analysis of how such networks can be optimized using state-of-the-art machine learning methods to improve resilience and performance under stress conditions. This case study not only gives our simulations its structural and operational setting but also roots the research in a context, which is representative of real-life situations and difficulties associated with gas network management.

5 Results and Discussion

In this section, the results and analysis of the Q-learning algorithm used to control gas network operations in cold spells are shown. Four types of graphical data are discussed: Q-value convergence, action frequency, distribution of pressure and a performance comparison with sub-optimal actions. The analysis is centered on the efficiency of Q-learning in the optimization of decision-making and stress management across the network. Furthermore, this section describes the simplifications, which were used in the simulations, and suggests potential areas for future improvements based on the present results.

5.1 Results

5.1.1 Pressure Distribution

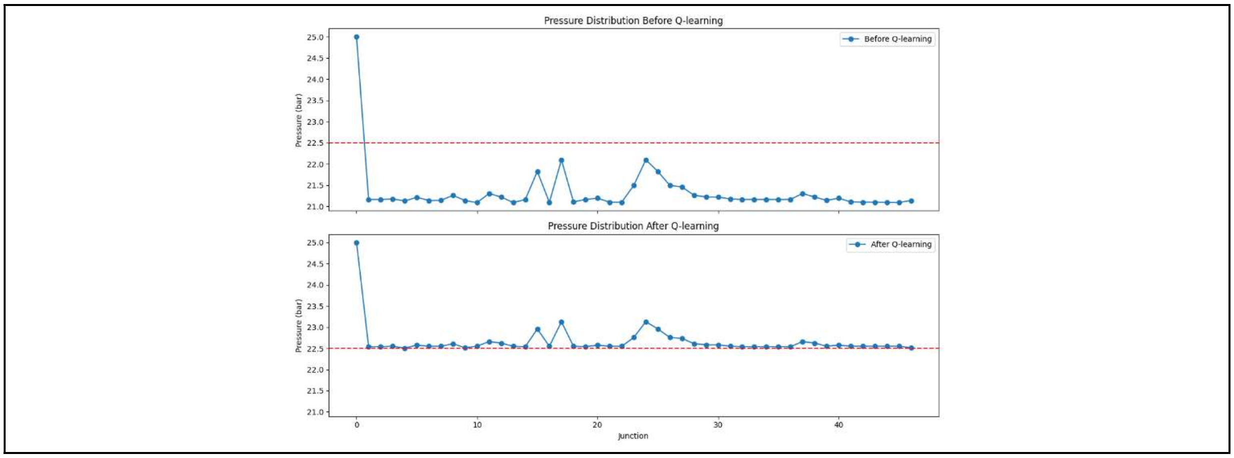

Fig. 10 Pressure distribution plot before and after the use of Q-learning

The pressure distribution plots (Fig. 10) before and after Q-learning exhibit the effectiveness of the agent in stabilizing network pressures within the desired thresholds. Initially, the pressure differentials across junctions were marked as an indication of the network's performance variability. Upon using Q-learning strategies, the pressure was normalized considerably, as all junctions started to follow the reference pressure of the external grid closely. This shows the agent's ability to adaptively tune actions and optimize the network under operational constraints making sure that pressures are within the set range of 10% of the reference value.

5.1.2 Q-value Convergence

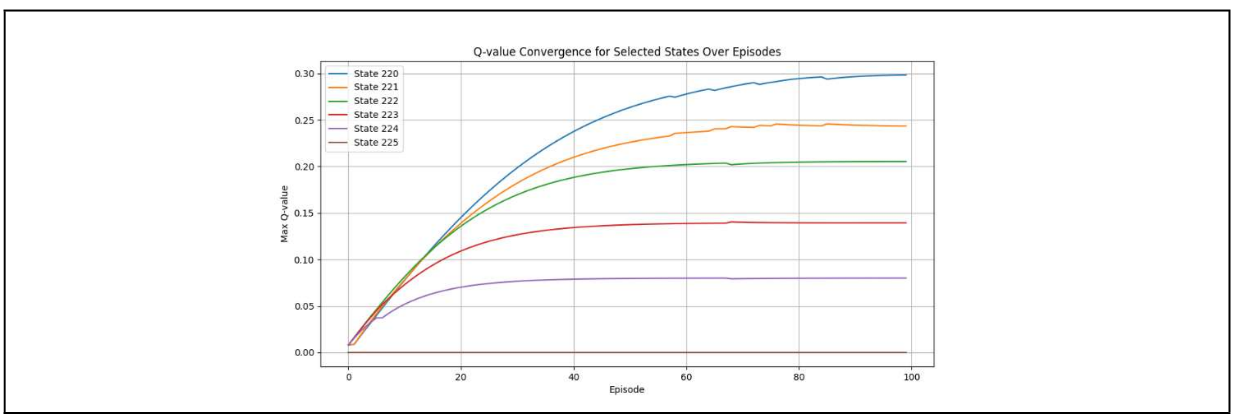

Fig. 11 Q-value convergence graph

The Q-value convergence plot (Fig. 11) shows the agent's understanding of the best actions over multiple episodes. Each line represents a separate state in the gas network, with each state connected to a particular minimum pressure level, which has been set by pressure range discretization. However, as episodes progress the Q-values for each state start to grow which is a signal of the agent's improved ability in evaluating the best actions to be taken in each state. This brings about convergence, which represents the learning process where the agent arrives at a better understanding of which actions maximize pressure stabilization within the network showcasing the effectiveness of the Q-learning algorithm in modifying and improving strategies with time.

5.1.3 Action Frequency

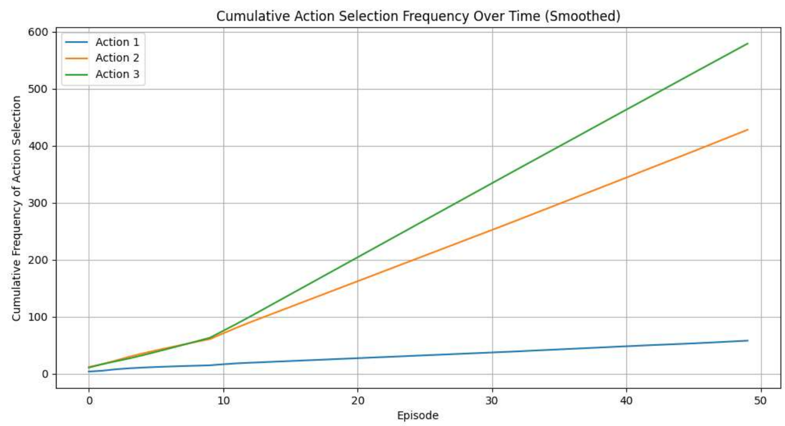

Fig. 12 Cumulative action frequency plot

The cumulative action selection frequency plot (Fig. 12) depicts the decision-making changes the Q-learning agent undergoes over several episodes. As episodes continue, it is evident that specific actions are increasingly preferred which points to the agent's efficiency in coming up with better strategies in order to stabilize the network pressure. Actions corresponding to sources at specific locations and rates of flow that give higher network pressures on a consistent basis start to dominate. This trend specifies the learning process of the agents that optimizes choice of action to lead to the desired pressure levels all over the network in an efficient manner.

5.1.4 Comparison of Q-learning vs Sub-optimal Action Selection

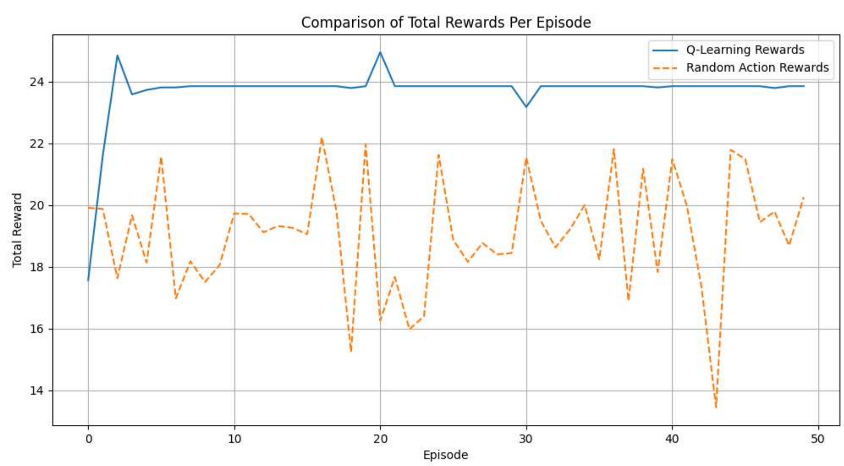

Fig. 13 Performance comparison of q-learning agent vs sub-optimal action selection

The figure representing the comparison of the total rewards per episode (Figure 13) demonstrates the advantage of the Q-learning strategy over a random action selection. With every consecutive episode, the Q-learning agent gets increasingly higher rewards, thus confirming its ability to learn and take decisions, which optimize the pressure levels within the network. The trend of increasing rewards being stable in the latter episodes means that the agent has understood the best actions to force the network pressure to be within the desired thresholds. This development in performance illustrates the agent's ability to adjust and to tune its policy in a changing environment.

5.2 Discussion

The application of Q-learning has proved to be very efficient at optimizing gas network pressures during cold spells. The Q-value convergence graph (Fig. 10) clearly shows a stepwise learning process of optimal actions by the Q-learning agent at different network states, exhibiting strong capture of pressure control techniques within the system. This learning trajectory is reflected in the stability of the network pressures which, as shown in the pressure distribution charts (Fig. 12), were sustained consistently within the target operating range after the learning process.

These results highlight the capability of Q-learning to improve control of complex network operations in a changing environment. The adaptability of the model and continuous strategy improvement thus emphasize its ability to improve operational efficiency and reliability, particularly during times of peak demand or adverse weather conditions. Thus, the implementation of AI-based solutions points towards opportunities for improvement of smarter, more adaptive network management systems, which respond to demand or supply changes, result in fewer risks, and increase overall service stability.

5.3 Future Improvements

The application of Q-learning to simulate the pressure of gas networks was achieved through the inclusion of certain simplifications. Due to the weakness of Q-learning in continuous state spaces, discretization of the state space was employed, concentrating on the minimum pressure at network junctions. This method is a simplification of the complex dynamics of a real gas network, but subtle details could be lost which could be incorporated in a continuous state space model. In addition, the simulation assumed the ability to add several sources to one location, which is a practical simplification aimed to increase the influence of sources on the pressure levels of the network.

Looking forward, improving the model to include a continuous state space could provide a number of benefits. Applying advanced methods such as Deep Q-Networks (DQNs) would allow the system to function at a higher level of detail providing greater control and richer insights. Further, the broadening of the action space would enable the Q-learning agent to identify source locations and adjust flow rates, thus, eliminating the requirement to follow pre-defined positions. Adding features enabling dynamic control over network valves would further strengthen adaptability and resilience of the system. These improvements would allow dynamic control based on live information and circumstances, evolving into an autonomous, intelligent network management system. These improvements are anticipated to highly refine operational tactics and results in the practical environments, providing a way to more reactive and effective infrastructure management.

6 Conclusion

In concluding, this study successfully employed Q-learning to enhance the management of gas pipeline pressures during cold spells, highlighting the potential of machine learning technologies in management of critical infrastructure. The simulation, executed through a Python-based Q-learning class, demonstrated the capability of AI to predict and manage complex network behaviors effectively. Through the adjustment of the action space and optimization of strategy using real-time simulations, significant improvements in network resilience and operational efficiency were observed. These findings emphasize the importance of integrating advanced machine learning techniques into utility management to anticipate and mitigate the challenges posed by extreme weather conditions and demand surges. Future work could extend these methodologies to more complex network models and compare different AI techniques to enhance predictive accuracy and operational robustness. This research paves the way for more sophisticated AI applications in infrastructure management, promising enhanced reliability and safety in the face of increasing environmental unpredictability.

7 References

[1] Sistema Nacional de Proteccion Civil (SINAPROC), “National Emergency Plan,” no. July, 2023, [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/15003161%5Cn.

[2] Z. Yang *et al.*, “Resilience of Natural Gas Pipeline System: A Review and Outlook,” *Energies*, vol. 16, no. 17, 2023, doi: 10.3390/en16176237.

[3] R. Carvalho, L. Buzna, F. Bono, M. Masera, D. K. Arrowsmith, and D. Helbing, “Resilience of natural gas networks during conflicts, crises and disruptions,” *PLoS One*, vol. 9, no. 3, pp. 1–9, 2014, doi: 10.1371/journal.pone.0090265.

[4] X. Li, H. Su, J. Zhang, and N. Yang, “A Robustness Evaluation Method of Natural Gas Pipeline Network Based on Topological Structure Analysis,” *Front. Energy Res.*, vol. 9, no. September, pp. 1–14, 2021, doi: 10.3389/fenrg.2021.730999.

[5] Intergovernmental Panel on Climate Change, *Weather and Climate Extreme Events in a Changing Climate*. 2023.

[6] Y. C. Liang *et al.*, “The Weakening of the Stratospheric Polar Vortex and the Subsequent Surface Impacts as Consequences to Arctic Sea Ice Loss,” *J. Clim.*, vol. 37, no. 1, pp. 309–333, 2024, doi: 10.1175/JCLI-D-23-0128.1.

[7] R. Xiao, T. Zayed, M. A. Meguid, and L. Sushama, “Improving failure modeling for gas transmission pipelines: A survival analysis and machine learning integrated approach,” *Reliab. Eng. Syst. Saf.*, vol. 241, no. May 2023, p. 109672, 2024, doi: 10.1016/j.ress.2023.109672.

[8] B. Awuku, Y. Huang, and N. Yodo, “Predicting Natural Gas Pipeline Failures Caused by Natural Forces: An Artificial Intelligence Classification Approach,” *Appl. Sci.*, vol. 13, no. 7, 2023, doi: 10.3390/app13074322.

[9] D. Zhou *et al.*, “Dynamic simulation of natural gas pipeline network based on interpretable machine learning model,” *Energy*, vol. 253, p. 124068, 2022, doi: 10.1016/j.energy.2022.124068.

[10] B. Y. Hong *et al.*, “A liquid loading prediction method of gas pipeline based on machine learning,” *Pet. Sci.*, vol. 19, no. 6, pp. 3004–3015, 2022, doi: 10.1016/j.petsci.2022.05.002.

[11] Y. Yang, S. Li, and P. Zhang, “Data-driven accident consequence assessment on urban gas pipeline network based on machine learning,” *Reliab. Eng. Syst. Saf.*, vol. 219, no. November 2021, p. 108216, 2022, doi: 10.1016/j.ress.2021.108216.

[12] K. Mira, F. Bugiotti, and T. Morosuk, “Conversion and Management,” 2023.

[13] Y. Li, F. Bu, Y. Li, and C. Long, “Optimal scheduling of island integrated energy systems considering multi-uncertainties and hydrothermal simultaneous transmission: A deep reinforcement learning approach,” *Appl. Energy*, vol. 333, 2023, doi: 10.1016/j.apenergy.2022.120540.

[14] S. Stavrev and D. Ginchev, “Reinforcement Learning Techniques in Optimizing Energy Systems,” *Electronics*, vol. 13, no. 8, p. 1459, 2024, doi: 10.3390/electronics13081459.

[15] “Creating a simple network-- pandapipe tutorials,” *GitHub*, 2023. https://github.com/e2nIEE/pandapipes/blob/master/tutorials/creating_a_simple_network.ipynb.

[16] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “Networks-- pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024. https://pandapipes.readthedocs.io/en/latest/networks.html.

[17] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “Junction Component--pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024. https://pandapipes.readthedocs.io/en/latest/components/junction/junction_component.html.

[18] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “Pipe Component-- pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024. https://pandapipes.readthedocs.io/en/latest/components/pipe/pipe_component.html.

[19] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “Sink Component-- pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024. https://pandapipes.readthedocs.io/en/latest/components/sink/sink_component.html.

[20] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “External Grid Component-- pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024. https://pandapipes.readthedocs.io/en/latest/components/ext_grid/ext_grid_component.html.

[21] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “Pipeflow Procedure-- pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024. https://pandapipes.readthedocs.io/en/latest/pipeflow/pipeflow_procedure.html.

[22] Nisha Arya, “A Beginner’s Guide to Q Learning,” *KDnuggets*, 2022. https://www.kdnuggets.com/2022/06/beginner-guide-q-learning.html.

[23] Baeldung Editorial Team, “Epsilon-Greedy Q-learning,” *Baeldung on Computer Science*, 2023. https://www.baeldung.com/cs/epsilon-greedy-q-learning.

[24] P. R. Montague, *Reinforcement Learning : An introduction*, vol. 3, no. 9. 1999.

[25] Texas A&M University Engineering Experiment Station, “Synthetic Gas-Electric Test case for the Travis 150 System,” *Electric Grid Test Case Repository*, 2024. https://electricgrids.engr.tamu.edu/synthetic-gas-electric-test-case-for-the-travis-150-system/.

[26] U. of K. Fraunhofer Institute for Energy Economics and Energy System Technology (IEE), “Fluids-- pandapipes 0.10.0 documentation,” *pandapipes.readthedocs.io*, 2024.

https://pandapipes.readthedocs.io/en/latest/fluid_properties/fluids.html.

[27] F. Energy and R. Commission, “Winter Energy Market and Electric Reliability Assessment,” 2024.

[28] U.S. Energy Information Administration (EIA), “Natural Gas Monthly - April 2024 With Data for February 2024,” *Energy Information Administration*, 2024. https://www.eia.gov/naturalgas/monthly/.

[29] PetroWiki Editorial Team, “Pressure drop evaluation along pipelines,” *PetroWiki*, 2024. https://petrowiki.spe.org/Pressure_drop_evaluation_along_pipelines.