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Exploiting the line pack potential of gaseous CO_2 pipelines

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ABSTRACT

Carbon dioxide transport is a critical component of the carbon capture and sequestration (CCS) supply chain. Given the substantial energy requirements and dispersed locations of CCS facilities, optimizing pipeline operations is critical to minimize costs. Although CO_2 in dense phase is typically favored for long-distance transport, gaseous phase transport is also a possibility for shorter distances and volumes. This study models a gaseous CO_2 pipeline system. Since CO_2 gas pipelines provide the benefit of line packing, owing to gas compressibility, this work leverages it to maximize throughput in the presence of disturbances. Pipeline pressures within each segment are perceived as an inventory (i.e. form of storage) and a model predictive control (MPC) formulation for optimal inventory management is implemented to maximize throughput. This study applies the formulation to pipelines arranged in series and parallel. It effectively maximizes throughput and optimally drains pipeline pressures in the presence of an inlet flow rate disturbance.

Keywords: Process Control, Optimization, Nonlinear Model Predictive Control, Carbon Dioxide Gas Pipelines

INTRODUCTION

CO_2 transport via pipelines is an integral component of carbon capture and sequestration (CCS) due to the spatial distribution of capture and sequestration sites. Additionally, the urgency for decarbonization necessitates minimizing the cost and energy intensity of CO_2 transport especially since it accounts for approximately 25% of total CCS costs [1]. One approach to minimize operational costs is to exploit the line pack potential of gaseous CO_2 pipelines [2] to maximize throughput in the presence of shifting bottlenecks. Bottleneck here refers to a process constraint preventing further increase in throughput. In essence, this study investigates how pipeline pressures can be used as buffers to delay the impact of disturbances on throughput. Thus, a model predictive approach for inventory (pipeline pressure) control based on Turan, et al. [3] and Kumaraswamy, et al. [4] is implemented in this study to maximize throughput in gaseous CO_2 pipelines.

Although CO_2 can be transported in various other forms (e.g. ships, trucks, and rail), pipeline transport is one of the most mature and cost-effective technologies for large-scale transport [1, 5]. CO_2 is typically transported in liquid or dense phase at high-pressure over long distances as this is cost-effective [6]. Lower pressures result in lower densities and higher pressure drops. However, gaseous CO_2 pipelines are a possibility for shorter distances with operating pressures below 48 bar [7]. For example, OGE is developing a 28 km pipeline in Germany from Lägerdorf to Brunsbüttel, operating at a design pressure of 40 bar [8]. With the development of industrial clusters for gathering captured CO_2, short distance and low volume low-pressure gaseous pipelines might be preferable for certain pipelines. Several industrial clusters for gathering captured CO_2 are in development including industrial sources in the Oslo-fjord region [9], the Coda terminal [10], and the industry in Rotterdam [11]. Such industrial clusters are expected to experience disturbances in CO_2 capture flow rates and injection flow rates, owing to the scale and interconnectedness of the system [12]. The proposed control approach in this study is therefore well suited for throughput maximization within industrial clusters, where variability in capture and injection rates must be effectively managed.

Within the field of CO_2 transport and injection research, there has been great emphasis on steady-state optimal supply-chain design. Since several CCS projects have been staged for construction and implementation in the upcoming years, optimal design of transportation networks to minimize costs is a critical challenge. Studies have attempted to address this challenge considering

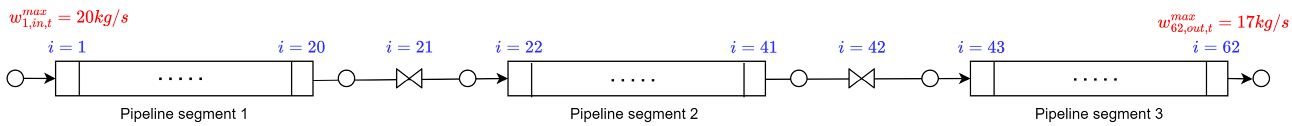

Figure 1. Sequential arrangement of pipelines (Case A)

different geographical scales, transport modes, and model complexity. Zhou, et al. [13] provide a detailed review of superstructure-based models for CCS pipeline network design. Ismail, et al. [14] review several studies centered on injection optimization and well control strategies incorporating detailed reservoir modelling.

Although there have been studies carrying out dynamic simulations to investigate the hydraulic and thermodynamic behavior of CO_2 in pipelines [15, 16], few studies have focused on methods for control and operational optimization for CO_2 transport and injection [17, 18]. This is the focus of the present paper.

Pressures within CO_2 pipelines can vary significantly depending on throughput, temperature, and transportation distance. Martynov, et al. [2] developed a correlation estimating line packing times for CO_2 pipelines under various pressure and distance conditions. The line packing time can vary between 30 mins to 2 hours for pipeline inlet pressures between 20 to 120 bar. The pressure threshold within the pipeline was set to 10 bar above the inlet pipeline pressure. This emphasizes the operational flexibility that CO_2 pipelines can offer in the presence of bottlenecks. It underscores the significance for investigating control strategies to optimally operate low-pressure gaseous CO_2 pipelines. While control strategies for optimal operation of gaseous CO_2 pipelines remains largely unexplored, it has been studied for natural gas pipeline networks [19–21].

Given the scale and interconnectedness of natural gas pipeline networks, which is also expected for CO_2 pipeline networks, studies have investigated the application of model predictive control (MPC) strategies to optimally operate such networks. Baumrucker, et al. [19] developed a non-linear dynamic model for mass flow and pressure in a natural gas pipeline network. An economic MPC was implemented to optimize compressor operation in the presence of varying electricity prices. However, to our knowledge, no study has adopted an optimal inventory control approach to the gas pipeline network process. In this study, pipeline pressures are treated as inventory and an inventory control formulation [3] is applied to maximize throughput from the gas pipeline while respecting pressure constraints.

Inventory control has been explored previously in the literature [22]. The term inventory is defined as any unit with hold-up (e.g. pressure, level). Some work has focused on inventory control strategies for bottleneck isolation. This concept can be simply explained as follows. Consider a pipeline transporting CO_2 from a capture site to a terminal for further transportation to a sequestration site. Additionally, consider that the inlet and outlet flow rates for this pipeline are determined by an optimizer. The optimizer is built on the principle that maximizing CO_2 transport to the terminal equates profit maximization. If a CO_2 capture plant were to shut down temporarily, the optimal inventory management strategy would be to maximize the pipeline outlet flow rate until pressures in the pipeline are at their lower limit. Subsequently, outlet flow rates would be lowered. This approach to isolate bottlenecks in a process has been described in the literature and applied to liquid tank levels. A PID control strategy, termed as the bidirectional control strategy, was formulated in Zotică, et al. [23] for sequential liquid tanks. An MPC approach achieving similar objectives was proposed by Turan, et al. [3] and Kumaraswamy, et al. [4].

In this work, an MPC inventory control approach is selected owing to the non-linearities, scale, and multi-input-multi-output nature of a CO_2 gas pipeline network. The inventory control formulation approach from Turan, et al. [3] is applied to two arrangements of CO_2 gas pipelines – sequential and parallel. We seek to investigate the effectiveness of this control strategy to optimally operate a CO_2 gas pipeline network.

MODELLING

The non-linear dynamic model in this paper is taken and adapted from a natural gas pipeline network model in [19]. We follow their exposition closely. Consider a pipeline network consisting of pipeline arcs, P, and choke valves, V. These elements are modelled as a system of arcs connected by nodes. Each arc in the network is indexed by $\forall i \in A$, with its endpoints identified by $\forall k \in \{in, out\}$, and nodes indexed by $\forall j \in J$. For the purposes of this paper, we define the term "pipeline segment" as a control volume formed by aggregating multiple pipeline arcs connected in series. An overview of the two pipeline arrangements investigated in this study are shown in Figures 1 and 2, where the distinction between pipeline arcs and segments are illustrated in these figures. The time horizon is partitioned into several discrete intervals, indexed by $t \in T$, each corresponding to one time step. Material and momentum conservation equations are imposed at arc endpoints. We also assume that each arc

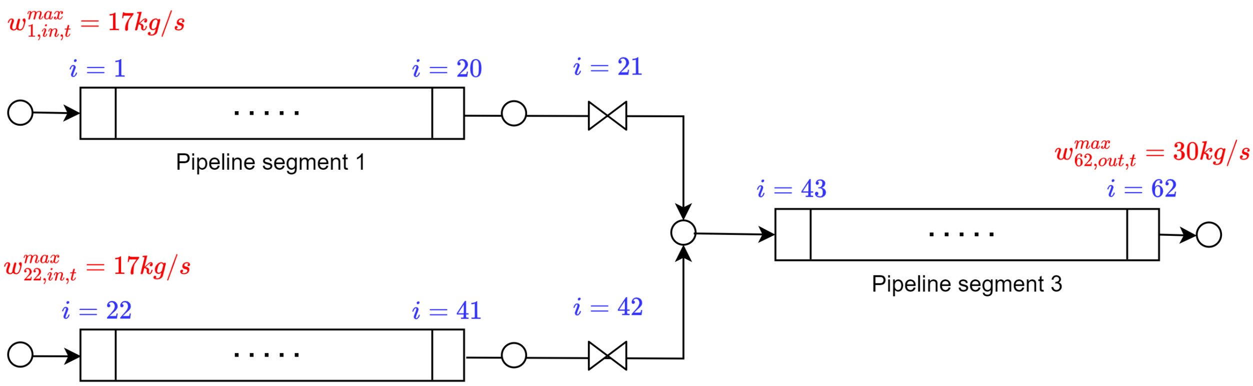

Figure 2. Parallel arrangement of pipelines (Case B)

endpoint shares the same pressure as its connected node. Additionally, no mass accumulation occurs at the nodes.

The governing equations are presented below. The material balance equation (eq. 1) is written in integrated form and approximated using the trapezoidal rule.

$$V_i\left(\overline{\rho}_{i,t+1} - \overline{\rho}_{i,t}\right) = \frac{1}{2}[(w_{i,in,t} - w_{i,out,t}) + (w_{i,in,t+1} - w_{i,out,t+1})]\Delta t,$$

$$\forall i \in \mathrm{P},\ t = 1, \dots, T-1. \quad (1)$$

The material balance equation determines the change in average pipeline arc density, $\overline{\rho}_{i,t}$ ($\frac{kg}{m^3}$), within a pipeline arc of volume, V_i (m^3). This is dependent on the flows entering, $w_{i,in,t}$ ($\frac{kg}{s}$), and leaving, $w_{i,out,t}$ ($\frac{kg}{s}$), the pipeline arc. Pressure drop due to friction is incorporated by implementing the one-dimensional plug flow equation (eq. 2) which calculates the pressure differential, $\left(\frac{dp}{dz}\right)_{i,k,t}$ ($\frac{bar}{m}$), at pipeline arc endpoints.

$$\left(\frac{dp}{dz}\right)_{i,k,t} = -\frac{f_{i,k,t}\, w_{i,k,t}^2}{2D_i A_i^2 \rho_{i,k,t}\, 10^5},$$

$$\forall \mathrm{i} \in \mathrm{P}, \mathrm{t} = 2, \dots, \mathrm{T}. \quad (2)$$

Note that only horizontal pressure variations along the pipeline (z) are considered and gravitational pressure losses are neglected under the assumption of perfectly horizontal pipelines. The frictional pressure drop is governed by flow-dependent parameters - specifically the friction factor, $f_{i,k,t}$, flow rate, $w_{i,k,t}$, and density, $\rho_{i,k,t}$- as well as pipeline characteristics, namely the cross-sectional area, A_i (m^2), and diameter, D_i (m). Each pipeline arc is assumed to have a diameter of 0.4m. A Reynolds-dependent friction factor is computed based on the Haaland correlation (eq. 3). Absolute roughness, ϵ (m), is assumed to be $2 \times 10^{-5}\ m$. Since CO_2 exhibits non-ideal gas behavior over the pressure range considered in this study, we have modified the dynamic model by Baumrucker, et al. [19] to incorporate a real gas formulation. Fluid properties – density and viscosity – for each pipe segment is computed using a real gas formulation, where the compressibility factor is represented by a second-order polynomial fitted from regression. The polynomial fit is valid over a range of 5 to 45 bar, corresponding to expected operating ranges of gaseous CO_2 pipelines.

$$\frac{1}{\sqrt{f_{i,k,t}}} = -1.8 \log_{10}\left[\left(\frac{\epsilon/D_i}{3.7}\right)^{1.11} + \frac{6.9}{Re_{i,k,t}}\right]$$

$$\forall \mathrm{i} \in \mathrm{P}, \mathrm{t} = 2, \dots, \mathrm{T}. \quad (3)$$

Pressure changes along pipeline arcs with length, L_i, of 1 km, are described using a 2-point Lobatto collocation scheme. This results in expressions for the outlet pressure and average pressure of each arc (eq. 4 and 5 respectively). A detailed derivation can be found in Baumrucker, et al. [19].

$$p_{i,\,\mathrm{out},t} = p_{i,\,\mathrm{in},t} + \frac{L_i}{2}\left[\left(\frac{dp}{dz}\right)_{i,\,\mathrm{in},t} + \left(\frac{dp}{dz}\right)_{i,\,\mathrm{out},t}\right],$$

$$\forall \mathrm{i} \in \mathrm{P}, \mathrm{t} = 2, \dots, \mathrm{T}. \quad (4)$$

$$\overline{p}_{i,t} = \frac{p_{i,\,\mathrm{in},t} + p_{i,\,\mathrm{out},t}}{2} + \frac{L_i}{12}\left[\left(\frac{dp}{dz}\right)_{i,\,\mathrm{in},t} - \left(\frac{dp}{dz}\right)_{i,\,\mathrm{out},t}\right],$$

$$\forall \mathrm{i} \in \mathrm{P}, t = 2, \dots, T. \quad (5)$$

MPC CONTROL FORMULATION

Having presented the dynamic model, we now define the control problem. In this study, we apply an inventory control MPC formulation to maximize system outflow and weighted inventories [3]. We seek to maximize the outlet flow rate from a pipeline system and the weighted pressure within each pipeline segment,

$$\min J = \sum_{t=2}^{T}\Bigg\{\underbrace{\sum_{i\in\mathcal{O}} \gamma^t \alpha_i\left(w_{i,out,t} - w_{i,out,t}^{max}\right)^2}_{Outflow\ max.} -$$

$$\left.\underbrace{\sum_{i\in S}\gamma^t\beta_i p_{i,in,t}}_{Inventory\ max.}\right\} + \underbrace{R}_{penalty\ term} \quad (6)$$

In accordance with the weight selection guidelines in Turan, et al. [3], inventories closest to the system outflow are assigned the highest weights. This prioritization emphasizes a high pressure in the pipeline segment connected to the outlet. Consequently, bottleneck isolation can be achieved by sequentially lowering pipeline segment pressures, starting from the segment located furthest from the outlet. While it may initially appear counterintuitive – as flow is typically driven by a pressure gradient from the inlet to outlet – the pressure constraint limits are defined based on expected operating pressures. For instance, in Case A, the maximum pressure limit is highest in segment 1, followed by segments 2 and 3 respectively. By prioritizing inventory weights for segments near the outlet, these critical sections—essential for maintaining flow—are preferentially driven toward their maximum pressure limits.

For the purposes of this paper, pipeline pressures at the midpoint of each segment are chosen for maximization and control. Let us define S as the set of arc indices representing the midpoints of each pipeline segment and O as the set of arc indices representing system outflows. α_i and β_i represent the weights for system outflow and inventory (i.e. pressure) level maximisation. Throughput maximisation should be preferred over inventory maximisation to ensure inventories are drained in the presence of an upstream bottleneck. Hence, α_i is always assigned a larger value than β_i. The term, γ^t, is a time discount factor which prioritizes minimizing the objective function at earlier time steps.

A fundamental difference between liquid tank inventories, studied earlier and pipeline networks in the present work, is the requirement for boundary conditions. While liquid tank systems can be modelled using only flow rates, pipeline networks require at least one specified pressure boundary condition [24]. Hence, the outlet pressure is fixed in all simulations in this paper. Consequently, the outlet flow rate is determined by the system dynamics and MV movements. Hence, system outflow maximization in this study is formulated as a reference-tracking objective, unlike the liquid tank network where the system outflow is modelled as a manipulated variable (MV). As shown in Figures 1 and 2, the maximum outlet flow rate, $w_{i,out,t}^{max}$, is the setpoint for system outflow reference tracking.

The MVs in this system are the inlet flow rate(s) and valve openings between pipeline segments. These variables are assigned lower and upper bounds. Valves are assumed to have lower and upper bounds of 0.05 and 1 respectively. Lower bounds for the inlet flow rates are 5 $\frac{kg}{s}$ while upper bounds are shown on Figures 1 and 2.

The penalty term comprises of soft constraints on pipeline segment pressures and a damping term on network flow rates, with λ_1 and λ_2 denoting the corresponding penalty factors.

$$R = \lambda_1 \sum_{t=2}^{T}\sum_{i\in S}\left(p_{i,in,t}^{slack} + p_{i,in,t}^{surplus}\right) + \lambda_2 \sum_{t=2}^{T}\sum_{i=1}^{I}\gamma^t\left(w_{i,in,t} - w_{i,in,t-1}\right)^2 \quad (7)$$

Slack and surplus variables corresponding to violations of the minimum and maximum pressure limits are denoted as $p_{i,in,t}^{slack}$ and $p_{i,in,t}^{surplus}$. At the initial steady-state starting point, all pipeline segment midpoint pressures are at their maximum limit. The pressure range for each segment is defined as 4 bar. In addition, a damping term is introduced to penalize large fluctuations in pipeline flow rates across all arcs. This term promotes smoother MV movement and is included specifically in the pipeline pressure system. Unlike the liquid tank system explored in Turan, et al. [3], gas pipeline networks are sensitive to large and rapid changes in the MVs, which can cause pressure oscillations and instability. Thus, regulated MV movement is necessary. Moreover, inventory levels in gas pipeline networks are inherently coupled. While the liquid level in a tank depends only on its inlet and outlet flow rates, pressure variations in one pipeline segment affect flow rates and pressures across the entire network. Hence, the inclusion of a term to smooth MV movement is desirable.

RESULTS

The control strategy described above was implemented for two pipeline arrangements – sequential (Case A, Figure 1) and parallel with merger (Case B, Figure 2). In this study, the MPC receives pipeline pressure measurements at intervals of 1 km along the pipeline length. Simulations were carried out with a disturbance in the maximum allowable inlet flow rate to the pipeline at $t = 1h$. In this system, maximum flow rates for the inlet are assumed to be higher than the outlet to demonstrate both pipeline depressurization and pressurization as the bottleneck shifts between the outlet and inlet of the pipeline. Simulations begin at steady-state conditions with all pipeline segment midpoint pressures and the outlet flow rate maximized. Steady-state conditions are obtained by solving the steady-state form of the dynamic model presented above using a non-linear solver, Ipopt. The total simulated time is 22 hours with a time step of 5 minutes for all cases. All computations were performed on a 64-bit system with an Intel Core Ultra 5 135H processor (3.60 GHz) and 16 GB RAM. Each run requires approximately 5 to 10 mins. The dynamic model and MPC were formulated in the Julia programming language, using the JuMP optimization framework, and Ipopt as the non-linear programming solver.

Sequential arrangement of pipelines (Case A)

As shown in Figure 3, the inlet flow rate to pipe segment 1 reduces immediately because the upper bound on the inlet flow rate was reduced from 17 kg/s to 14 kg/s. Subsequently, the optimizer opens valve 1 to depressurize pipe segment 1. As the pressure in pipe segment 1 approaches its lower limit, valve 2 is opened and valve 1 is closed to depressurize pipe segment 2. Note that although pipe segment 3 has a lower limit of approximately 18 bar, it is limited by the outlet pressure boundary condition of 22 bar. Hence, pipe segment 3 is limited in its ability to depressurize. When further depressurization of the pipe segments is no longer possible, the valve openings reach a new steady-state such that the outlet flow rate reduces to 14 kg/s. At $t = 12h$, when the maximum inlet flow rate is restored to its original value of 20 kg/s, the optimizer increases the inlet flow rate and valve openings to maximize throughput and pressurize the system.

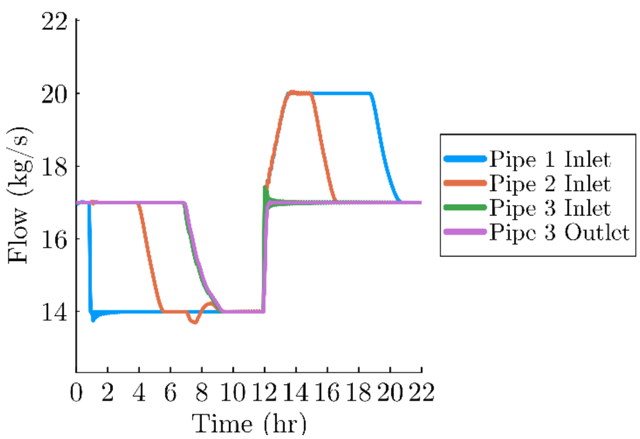

Figure 3. Case A – System flow rates

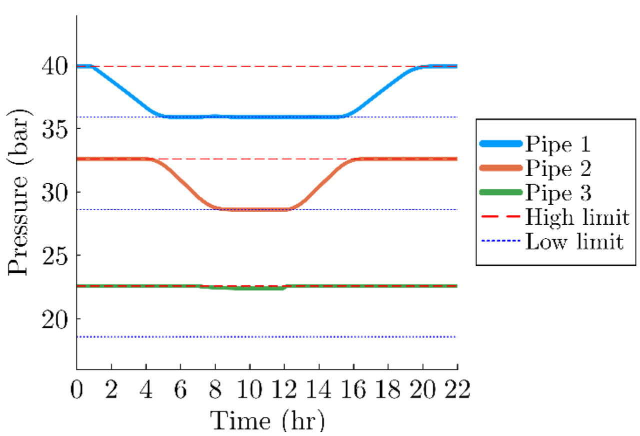

Figure 4. Case A – Pipeline segment midpoint pressures

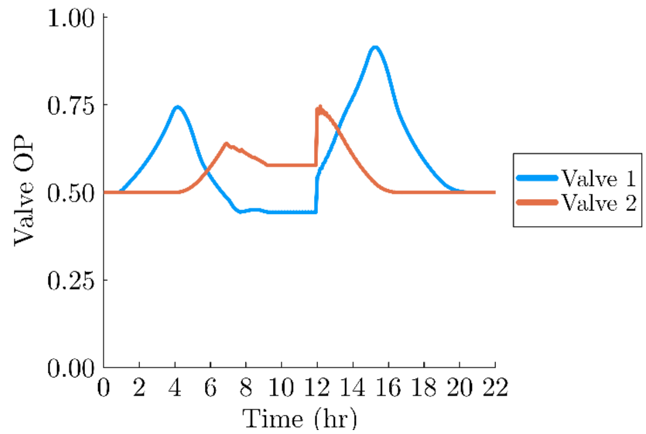

Figure 5. Case A – Valve openings

Parallel arrangement of pipelines (Case B)

For pipeline segments arranged in parallel, the MPC exhibits a similar response. At $t = 1h$, the upper bound on the inlet flow rate to pipe segment 1 is reduced to 10 kg/s. As a result, the optimizer reduces the inlet flow rate to pipe segment 1, increases the inlet flow rate to pipe segment 2, and manipulates the valve openings to depressurize pipe segment 1. Note that we assign the inventory weighting factors (β_i) such that the pressure in pipe segment 3 has the highest priority for maximisation, followed by pipe segment 2 and pipe segment 1. As shown in Figure 7, pipe segment 1 is depressurized followed by pipe segments 2 and 3. Subsequently, the outlet flow rate is also reduced when pipeline inventories are at their minimum pressures. When the upper bound on the inlet flow rate to pipe segment 1 is restored, the optimizer proceeds to maximize pressures in pipe segment 2 followed by pipe segment 1. The original steady-state throughput of 30 kg/s is restored.

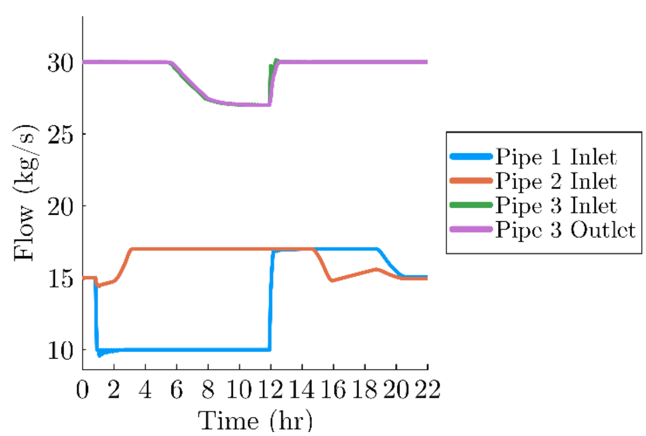

Figure 6. Case B – System flow rates

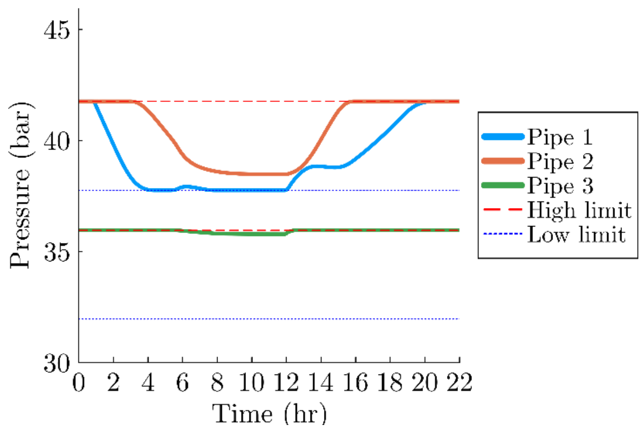

Figure 7. Case B – Pipeline segment midpoint pressures

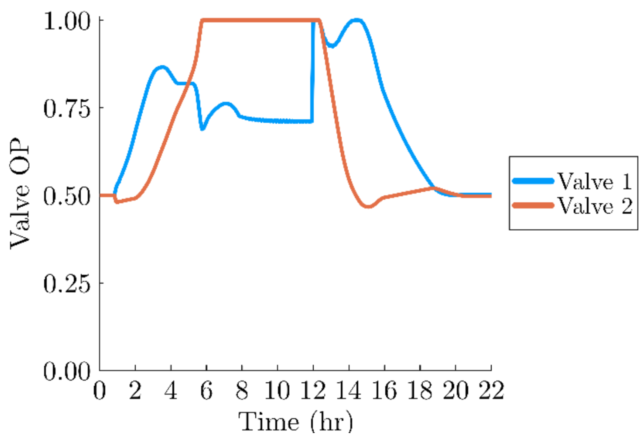

Figure 8. Case B – Valve openings

DISCUSSION

Although throughput maximisation can be economically desirable, this may come at a cost. Firstly, maximising throughput requires aggressive manipulation of the available degrees of freedom (see Fig. 5 and 8). However, this comes with operational wear and higher energy consumption. In systems where rapid MV movement is undesirable or destabilizing, some degree of optimality must be sacrificed. Hence, throughput maximisation should be pursued only as long as the marginal benefit of increased flow outweighs the marginal cost of achieving it.

From a practical perspective, the non-linear dynamic model developed in this study carries inherent assumptions that may limit its application to real-world conditions. Firstly, the pipeline network is assumed to be horizontal. However, real terrain is rarely uniform and incorporating a gravity term into the pressure drop formulation (eq. 2) can improve the model accuracy. In general, a key limitation in the proposed framework is model-plant mismatch, which is an inherent challenge in any model-based control formulation. Despite detailed pressure-flow modelling and the consideration of variable CO_2 compressibility, model-plant mismatch could still result in prediction errors and sub-optimal MV movement. In practice, however, this challenge is well-managed through state estimation where real-time measurements are used to continuously reconcile model predictions. Therefore, the inventory control formulation investigated in this study remains a viable and practical approach for throughput maximization in CO_2 gas pipeline networks.

CONCLUSION

In this paper, an optimal inventory MPC formulation for bottleneck isolation was implemented for CO_2 gas pipelines. The formulation sought to maximize throughput and the weighted sum of pipeline pressures. The formulation was applied with modifications, including the addition of a pressure boundary condition to accommodate pressure and flow dynamics in a pipeline. A flow damping term was also incorporated to ensure regulated MV movement as well as stable flow and pressure variations. Two arrangements of pipelines – sequential and parallel – were investigated and the MPC effectively maximized throughput in the presence of an inlet flow rate disturbance. Future work will extend the application of this inventory control MPC formulation for throughput maximization to larger-scale and more complex low pressure CO_2 gas pipeline networks.

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REFERENCES

1. Alcalde J. Transportation of CO2 [Internet]. Drax Group Plc; 2025. https://www.drax.com/wp-content/uploads/2025/06/DR1907-6_Transportation-of-CO2_GB_V002.pdf
2. Martynov SB, Porter RTJ, Mahgerefteh H. Estimating the line packing time for pipelines transporting carbon dioxide. Carbon Capture Science & Technology 11:100188 (2024). https://doi.org/10.1016/j.ccst.2023.100188
3. Turan EM, Skogestad S, Jäschke J. Model predictive control for bottleneck isolation with unmeasured faults. IFAC-PapersOnLine 58:767-774 (2024). https://doi.org/10.1016/j.ifacol.2024.08.430
4. Kumaraswamy A, Turan EM, Jäschke J. Optimal inventory control for bottleneck isolation in general processes. Journal of Process Control 155:103557 (2025). https://doi.org/10.1016/j.jprocont.2025.103557

5. Svensson R, Odenberger M, Johnsson F, Strömberg L. Transportation systems for co2—application to carbon capture and storage. Energy Conversion and Management 45:2343-2353 (2004). https://doi.org/10.1016/j.enconman.2003.11.022
6. Onyebuchi VE, Kolios A, Hanak DP, Biliyok C, Manovic V. A systematic review of key challenges of CO2 transport via pipelines. Renewable and Sustainable Energy Reviews 81:2563-2583 (2018). https://doi.org/10.1016/j.rser.2017.06.064
7. Metz B, Davidson O, Coninck H de, Loos M, Meyer L. IPCC special report on carbon dioxide capture and storage [Internet]. Intergovernmental Panel on Climate Change; 2005. https://www.ipcc.ch/report/carbon-dioxide-capture-and-storage/
8. OGE. CLB pipeline construction project [Internet]. https://oge.net/en/press-public-information/construction-projects/current-construction-projects-co2/clb-pipeline-construction-project
9. Equinor. Northern lights [Internet]. https://www.equinor.com/energy/northern-lights
10. Carbfix. A terminal coda [Internet]. https://www.carbfix.com/operations/codaterminal
11. Porthos. CO2 reduction through storage under the north sea [Internet]. https://www.porthosco2.nl/en/
12. Spitz T, Avagyan V, Ascui F, Bruce ARW, Chalmers H, Lucquiaud M. On the variability of CO2 feed flows into CCS transportation and storage networks. International Journal of Greenhouse Gas Control 74:296-311 (2018). https://doi.org/10.1016/j.ijggc.2018.04.008
13. Zhou C, Liu P, Pistikopoulos EN. Superstructure-based optimal design of pipeline network for CO2 transport in large-scale carbon capture and sequestration [Internet]. Computer aided chemical engineering. 2015. p. 225–52. https://doi.org/10.1016/B978-0-444-63472-6.00009-4
14. Ismail I, Gaganis V. Carbon capture, utilization, and storage in saline aquifers: subsurface policies, development plans, well control strategies and optimization approaches—a review. Clean Technol. 5:609-637 (2023). https://doi.org/10.3390/cleantechnol5020031
15. Yang Z, Fahmi A, Drescher M, Teberikler L, Merat C, Solvang S, et al. Improved understanding of flow assurance for CO_2 transport and injection. Proceedings of the 15th greenhouse gas control technologies conference. 2021.
16. Aursand P, Hammer M, Munkejord ST, Wilhelmsen Ø. Pipeline transport of CO2 mixtures: models for transient simulation. International Journal of Greenhouse Gas Control 15:174-185 (2013). https://doi.org/10.1016/j.ijggc.2013.02.012
17. Zhou L, Preindl M. Mpc-based harmonic injection techniques for reconfigurable single/three-phase inverters with grid neutral point connection. 2024 IEEE Transportation Electrification Conference and Expo (ITEC) :1-6 (2024). https://doi.org/10.1109/itec60657.2024.10598838
18. Xu Q, Zhang X, Sun B. Modeling and model predictive control of CO2 salt cavern storage process. Fuel 405:136633 (2026). https://doi.org/10.1016/j.fuel.2025.136633
19. Baumrucker BT, Biegler LT. MPEC strategies for cost optimization of pipeline operations. Computers & Chemical Engineering 34:900-913 (2010). https://doi.org/10.1016/j.compchemeng.2009.07.012
20. Gopalakrishnan A, Biegler LT. Economic nonlinear model predictive control for periodic optimal operation of gas pipeline networks. Computers & Chemical Engineering 52:90-99 (2013). https://doi.org/10.1016/j.compchemeng.2012.11.011
21. Moetamedzadeh HR, Khanmirza E, Pourfard A, Madoliat R. Intelligent nonlinear model predictive control of gas pipeline networks. Transactions of the Institute of Measurement and Control 41:4569-4589 (2019). https://doi.org/10.1177/0142331219864190
22. Aske EMB, Skogestad S. Consistent inventory control. Ind. Eng. Chem. Res. 48:10892-10902 (2009). https://doi.org/10.1021/ie801603j
23. Zotic? C, Forsman K, Skogestad S. Bidirectional inventory control with optimal use of intermediate storage. Computers & Chemical Engineering 159:107677 (2022). https://doi.org/10.1016/j.compchemeng.2022.107677
24. Çengel YA, Cimbala JM. Fluid mechanics: Fundamentals and applications [Internet]. McGraw-HillHigher Education; 2006. https://books.google.no/books?id=4RVEAQAAIAAJ