Optimizing Parallel Gas Compressor Operations Under Flow Disturbances

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Abstract: This paper investigates the operation of parallel compressors with variable speed drives to deliver gas at a desired flow rate while maintaining a target pressure at a common discharge header. We examine strategies to minimize energy consumption amid discharge flow fluctuations caused by changes in gas demand. Specifically, we model the energy consumption impact of varying operating points, accounting for efficiency sensitivity to flow. Our approach employs sample averaging to estimate expected energy usage under flow variations, which informs an offline surrogate objective function reflecting energy consumption under disturbances. This surrogate is subsequently used online in a deterministic nonlinear programming framework to approximate a stochastic optimization solution, determining optimal load distributions for the compressors. Additionally, we compare the proposed approach with an economic model predictive controller (eMPC). This approach first solves a tracking problem to stabilize header pressure, using compressor flows as manipulated variables, then redistributes the calculated control effort for the first step of the solution through an economic optimization. Both methods are implemented in a simulated pipeline compressor station, with a control hierarchy for station pressure, compressor flow, and anti-surge controllers. Simulation results, with and without flow disturbances, confirm that the stochastic load-sharing approach reduces energy consumption by 4.3% compared to a purely deterministic method, with the eMPC further improving efficiency by an additional 2.2%.

Keywords: Parallel compressors; variable speed drives; load sharing; stochastic optimization; economic model predictive control; energy efficiency.

1. INTRODUCTION

Gas compressors have long been essential in industrial applications such as gas storage (Silva and Camponogara, 2014), pipeline transport, (Borraz-Sánchez and Haugland, 2013), liquefied natural gas production (Mokhatab, 2013), compressed air production (Yuan et al., 2006), and air separation plants (Widell and Eikevik, 2010). Looking ahead, compressors will remain crucial for a wide range of process applications, including decarbonization efforts where they support CO_2 and H_2 pipelines (Kurz et al., 2023). At the same time, gas compression is an energy intensive process and improving energy efficiency can lead to significant economic gains. However, given the complexity of the system systematic approaches are required to realize these gains. In this work, we focus on optimizing energy efficiency for a compressor station undergoing flow disturbances.

In case of turbo-compressors and particularly centrifugal gas compressors, multiple compressors are often operated in parallel to provide more capacity and range than can normally be delivered by a single machine due to operational constraints such as compressor surge (Boyce, 2003). In the parallel setups, a total mass-flow, a group or station pressure ratio, a suction or discharge pressure set point can be defined and tracked by distributing the control effort among individual compressors. This can be achieved via cascade control arrangements, where for example an individual compressor flow target sent by a master controller is tracked by flow controllers for each compressor using variable speed drives (Liptak, 2005).

Allocating the total control effort to individual compressors to meet the operating objectives of parallel compressor groups is non-trivial. Equal load distribution is the most straightforward way to operate parallel compressors but even with nominally identical compressors, there is always some performance variation from one machine to the next (Blotenberg et al., 1984). Therefore other approaches are employed to distribute the load, with equal distance-to-surge being a common one (SIEMENS, 2012). However, these approaches neglect any impact of operating point selection on compressor efficiency and it is left to operators to make manual adjustments to utilize compressors efficiently.

Load Sharing Optimization (LSO) uses mathematical programming techniques to distribute compression effort among compressors by taking into account both operational objectives and constraints such as surge and can combine objectives such as delivering a desired gas flow and minimizing energy consumption (Rodrigues, 2022, Zhang et al., 2022). The main challenge in LSO implementations for compressor stations arises from two primary sources of uncertainty: uncertainty from process knowledge, mainly about the compressor performance, and uncertainty arising from external factors acting on the compressor system.

While existing literature has explored uncertainties related to compressor efficiency maps (Zagorowska et al., 2020, Kurz and Brun, 2012, Ahmed et al., 2022), uncertainties within the compressor network system as a whole remain largely under investigated. These uncertainties typically arise from disturbances that would affect stable and efficient load distribution across compressors. For instance, for gas transportation and distribution applications, sudden changes in gas demand can introduce significant disturbances. Similarly, in gas processing applications, fluctuations in upstream processes, such as changes in well conditions, feed composition, or processing parameters, can lead to unpredictable shifts in flow conditions and pressures (Tveit et al., 2004). When load sharing optimization is implemented as a Real-Time Optimization (RTO) layer, disturbances can cause discrepancies between the desired process operating point selected by the RTO and the actual operating conditions over the RTO sampling interval. This leads to a loss of overall system performance. To address this challenge, this work compares two approaches: (1) solving the RTO problem by accounting for implementation errors through a stochastic optimization approach, and (2) merging optimization objectives together with the control layer.

Following the introduction, the paper is organized as follows: In Section 2.1, we present a case study of a compressor station for the parallel operation of gas compressors, along with the methodology used to develop the stochastic load-sharing optimization and economic model predictive control solutions. In Section 3, we demonstrate the results of a simulation scenario to evaluate the performance of the different control and optimization strategies. Section 4 provides conclusions and suggestions for future work.

2. LOAD-SHARING IN A COMPRESSOR STATION

2.1 Compressor station

The compressor station configuration considered in this study consists of three centrifugal compressors (C1, C2, and C3) arranged in parallel as shown in Fig. 1 and Fig. 4. Control signals are represented by dashed lines, while gas flows are shown as solid lines. Each compressor has a Flow Controller (FC), which receives flow demand signals from the higher-level control layer as a set point. The FCs are implemented as PI controllers, which receive a flow measurement for the corresponding compressor and then sends a calculated target torque τ_i to the corresponding variable speed drive. Additionally, each compressor is protected by an Anti-Surge Controller (ASC), which receives input from several pressure and flow measurement points around the compressor and manipulates the ASC valve. In this work suction conditions are assumed to be stationary and therefore temperature measurements are not considered for ASC. In this study, we focus on maintaining a desired reference pressure in the discharge header that connects the compressors to the process equipment or a downstream pipeline. A change in header pressure indicates an imbalance between flow supply and demand, and the capacity of the compressors must be adjusted to keep the pressure at the desired operating level.

2.2 Compressor efficiency and power consumption

The power consumption of each compressor depends on the flow rate and the compressor's efficiency at that flow. For the i-th compressor, the power consumption P_i is:

$$P_i = \frac{y_{p,i}}{\eta_i}\dot{m}_i \tag{1}$$

where $\dot{m}_i$ represents the mass flow rate through the compressor, η_i is the efficiency at the current operating conditions, and $y_{p,i}$ denotes the polytropic head.

Mass flow rate uncertainty In ideal conditions, the actual flow through the compressor ${\dot{m}_i}^{\text{actual}}$ matches the target flow ${\dot{m}_i}^{\text{target}}$ obtained from LSO, with the pressure ratio Π_i adjusting according to the resistance curve of the system (Zagorowska et al., 2023). However, in practice, fluctuations in gas demand and flow, for instance due to the operation of low-level PI controllers, introduce variability around the target and the actual flow rate for the i-th compressor becomes:

$${\dot{m}_i}^{\text{actual}} = {\dot{m}_i}^{\text{target}} + \Delta\dot{m}_i \tag{2}$$

In this work, the disturbance in the actual compressor flow rate $\Delta\dot{m}_i$ is assumed to follow a normal distribution with standard deviation σ, $\Delta\dot{m}_i \sim \mathcal{N}(0, \sigma^2)$, with $\sigma = 10\,\text{kg/s}$.

Expected efficiency and power The variability in the mass flows affects both η_i and P_i, leading to variations in actual power consumption and efficiency. To illustrate the impact of uncertainty in the mass flow on compressor efficiencies, we plot the resulting nominal and expected efficiencies in Fig. 2 for compressors C1 to C3 along the system resistance curve. The plot shows that due to the steep change in efficiency for C1 the disturbances strongly influence the realized values of efficiency when operating at a given flow set point. Therefore, even though C1 appears to be very efficient and can be chosen by a naive approach to deliver a wide range of flows, the disturbances will lead to significant deterioration in performance.

The expected power $E[P_i]$ at a target flow rate ${\dot{m}_i}^{\text{target}}$ is approximated as the sample mean of N samples (Montgomery and Runger, 2010):

$$E[P_i({\dot{m}_i}^{\text{actual}})] \approx \frac{1}{N}\sum_{j=1}^{N} \frac{y_{p,i}\cdot\left({\dot{m}_i}^{\text{target}} + \Delta{\dot{m}_i}^{(j)}\right)}{\eta_i({\dot{m}_i}^{\text{target}} + \Delta{\dot{m}_i}^{(j)})} \tag{3}$$

where $\Delta{\dot{m}_i}^{(j)}$ denotes the j-th realization of the disturbance. In this work, we set $N = 1000$.

2.3 Compressor load sharing optimization

The load-sharing optimization aims to minimize the total power consumption across the compressors while meeting a specified total flow rate $\dot{M}_{\text{target}}$:

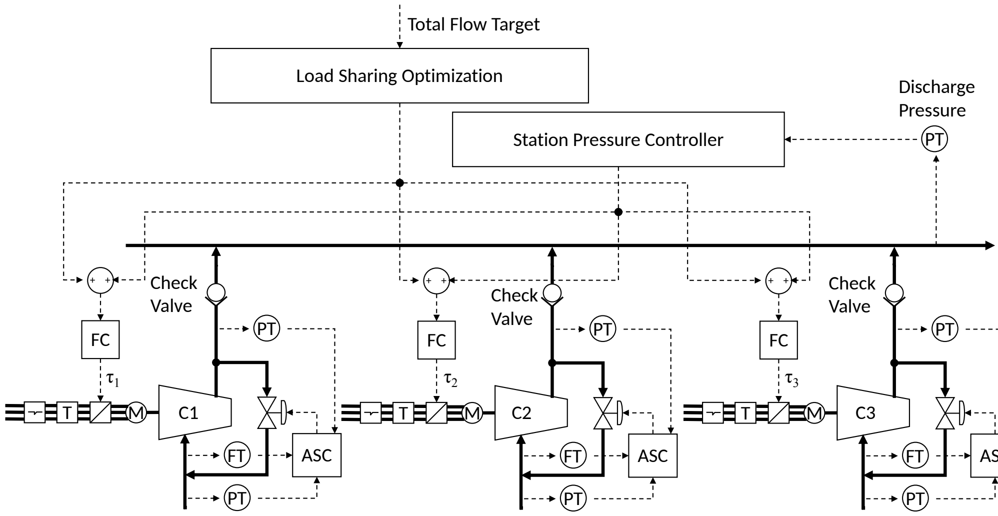

Fig. 1. This schematic shows how LSO, combined with the station pressure controller, allocates flow across compressors to maintain the target station mass flow rate while minimizing power consumption. The station pressure controller, based on the measured discharge pressure, sends commands to the Flow Controller (FC) to regulate compressor performance (adapted from SIEMENS (2012))

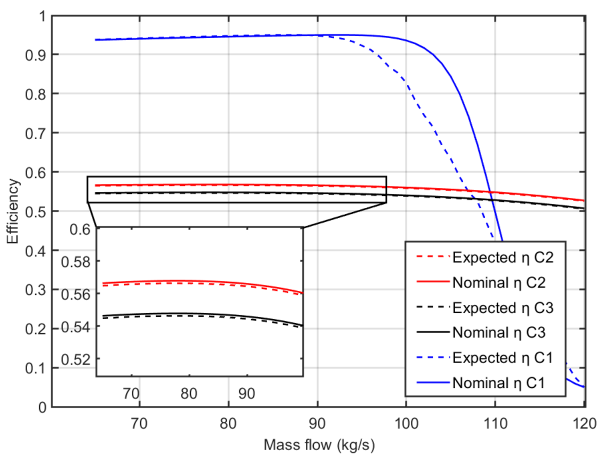

Fig. 2. Nominal and expected (under flow disturbances) values of efficiencies for the compressors considered in the compressor station case study

$$
\begin{aligned}
\min_{\dot m_1,\dot m_2,\dot m_3} \quad & \sum_{i=1}^{3} P_i(\dot m_i) \\
\text{subject to} \quad & \sum_{i=1}^{3} \dot m_i = \dot M_{\text{target}} \\
& \underline{\dot m}_i \le \dot m_i \le \overline{\dot m}_i, \quad i = 1,2,3
\end{aligned}
\tag{4}
$$

where $P_i(\dot m_i)$ is the power consumption of compressor i, and $\dot m_i$ is the compressor flow rate. The bounds $\underline{\dot m}_i$ and $\overline{\dot m}_i$ restrict the flow rates of each compressor to their allowable limits. We refer to the compressor flow rates $\dot m_i$ found at the solution as ${\dot m_i}^{\text{target}}$ as mentioned in Section 2.2.

Load sharing optimization under flow uncertainty We now extend (4) to account for flow uncertainty. Specifically, we aim to minimize the expected total power consumption across compressors, where the expectation is taken with respect to the distribution of flow disturbances. Using the linearity of the expected value over the summation operation, the modified objective function becomes:

$$\min_{\dot m_1,\dot m_2,\dot m_3} \sum_{i=1}^{3} E_{\Delta \dot m}\left[P_i(\dot m_i)\right] \tag{5}$$

where $E_{\Delta \dot m}$ is the expected power consumption, accounting for the variability introduced by flow disturbances $\Delta \dot m$ around each target flow.

Surrogate function approach To avoid the computational expense of evaluating the expectation (5) directly, we use Gaussian Process (GP) regression to build surrogate models to approximate the expected power consumption for each compressor. GPs were chosen as the surrogate model for approximating the expected power consumption because they are well-suited for handling noisy data, which arises naturally in our sampling-based procedure to compute expected power values (Ahmed et al., 2022). GP regression assumes that the values $P_i(m_i^j)$ corresponding to s different flows m_i^j, $j = 1, \dots, s$ are random variables, with joint Gaussian distribution for any finite s. In this work, we construct three separate GPs—one for each compressor—denoted as $\text{GP}_i(\dot m_i)$, where each GP takes the mass flow $\dot m_i$ as input and outputs an approximation of the expected power consumption $E_{\Delta \dot m}[P_i(\dot m_i)]$. The prior information about the functions P_i is defined by known mean ϕ_i and covariance k_i functions:

$$P_i(x) \sim \text{GP}_i(\phi_i(x), k_i(x, x)), \tag{6}$$

Following Rasmussen and Williams (2006), after R observations the mean of the prediction at a new point $\hat x$ is:

$$\mu_i(\hat x) = \psi_j(\hat x) + \mathbf{k}_R(\hat x)(\mathbf{K}_R + \mathbf{I}_R \sigma_\omega^2)^{-1}(\mathbf{G}_j - \mathbf{\Psi}_j), \tag{7}$$

where $\mathbf{G}_j$ is a vector of R observed noisy values, $\mathbf{\Psi}_j = [\psi_j(x_r)]_{r=1,\dots,R}$ is a vector of mean values of the past data, $j = 0, \dots, H$, the matrix $\mathbf{K}_R$ contains the covariance of

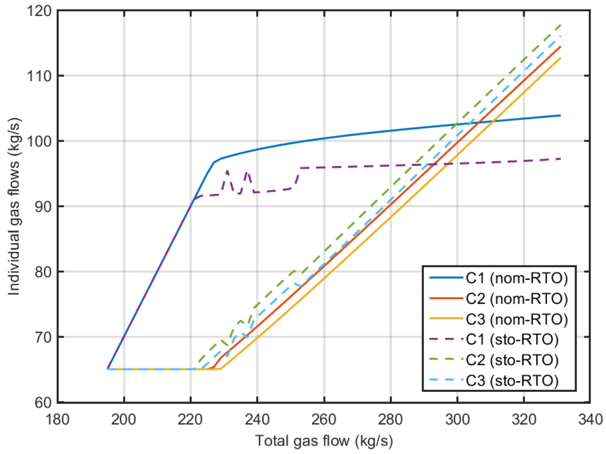

Fig. 3. Optimized values of individual compressor flows given a total gas flow target. Solid lines indicate the solutions obtained with the deterministic approach (nom-RTO). Dashed lines indicate the solution using expected power consumption estimates (sto-RTO).

past data, $k(x_a, x_b)$, $a, b = 1, \ldots, R$, $\mathbf{k}_R(\hat{x})$ contains the covariance between the new point and the past data, and $\mathbf{I}_R$ denotes identity matrix of dimension R.

We compute the expected power consumption over a range of mass flow rates $\dot{m}_i$ by sampling disturbances from the previously mentioned distribution in Section 2.2 and averaging the resulting power consumption values offline. These average values serve as training data for the GPs, allowing it to predict the expected power consumption continuously over the operating range.

During real-time optimization, the objective function from (4) is the sum of the mean predictions of the three GP models:

$$\min_{\dot{m}_1, \dot{m}_2, \dot{m}_3} \quad \sum_{i=1}^{3} \mu_i(\dot{m}_i) \tag{8}$$

where $\mu_i(\dot{m}_i)$ from (7) provides an approximation of the expected power consumption for compressor i.

Solutions of the optimization problems We numerically solve the resulting optimization problems for the nominal problem formulation and the formulation considering flow uncertainty with varying $\dot{M}_{\text{target}}$ over the considered operating range for the compressor station. The obtained solutions are plotted in Fig. 3, where $\dot{M}_{\text{target}}$ can be seen on the x axis and the optimized individual compressor flows $\dot{m}_i^{\text{target}}$ on the y axis, $i = 1, 2, 3$.

The optimization solutions considering the impact of flow uncertainties indeed cuts the loading of C1 earlier to avoid the excessive power consumption, which will arise from using this compressor at higher flow rates. Despite the GPs providing a smoother approximation of the expected power consumption compared to the sampled averages, we can still see artifacts of this noise in the lower total gas flow ranges, where the solution shows jumps.

Implementing load sharing optimization The proposed load sharing optimization solutions are implemented in the compressor station as shown in Fig.1. Both the nominal solution from (4) and the stochastic optimization with the objective (8) are implemented as an RTO layer, where they generate set points for the FCs of the compressors. The station discharge header pressure controller is implemented as a master PI controller and this controller also adjusts the set points of the FCs. These adjustments will be the main source of the flow variations $\Delta\dot{m}_i$ experienced by the compressors as shown in (2).

2.4 Load sharing via economic Model Predictive Control

We formulate an alternative solution as a simplified two-stage eMPC. In the first stage we use a discrete linear state-space model for the discharge header dynamics with header pressure y as output and compressor flows $u = [\dot{m}_i]_{i=1,\ldots,3}$ as inputs:

$$\begin{aligned} x(k+1) =& Ax(k) + Bu(k) + d(k) \\ y(k) =& Cx(k) + v(k) \end{aligned} \tag{9}$$

where A, B, C are constant transition, input, and measurement matrices, respectively [1]. The disturbances $d(k) \sim N(0, D)$ and $v(k) \sim N(0, V)$ are the associated process and measurement noise vectors and are modeled as uncorrelated, zero mean, white sequences with covariance matrices D and V. The system (9) is augmented with an integrator state and a steady-state Kalman Filter is designed for state estimation.

The pressure is controlled by solving at time k a constrained quadratic optimization problem over time horizon p, where the pressure y has to follow a desired reference trajectory $y^{\mathbf{ref}}$:

$$\begin{aligned} \min_{\Delta u_i} & \sum_{t=0}^{p-1} \Big(w_t^y (y(k+t+1|k) - y^{\mathbf{ref}}(k+t+1))^2 \\ & \quad + \sum_{i=1}^{M} w_t^{u_i} u_i^2(k+t+1|k) \Big) \\ \text{s.t. } & \underline{u}_i \le u_i \le \overline{u}_i \\ & \underline{\Delta u}_i \le \Delta u_i \le \overline{\Delta u}_i \\ & \Delta u_i(k|k) = 0 \\ & u_i(k|k) = u_i(k+m-1|k) \\ & u_i(t+k|k) = u_i(t+k-1|k) + \Delta u_i(t+k|k) \\ & t = 1, \ldots, p-1 \end{aligned} \tag{10}$$

where $M = 3$ is the number of compressors, w_t^y and $w_t^{u_i}$ are output and input weights, respectively, and m is the control horizon. For this paper, we chose $w_t^y = p = 100$, $m = 10$, $w_t^{u_i} = 1$. The decision variables $\Delta u_i(t+k|k)$, $t = 0, \ldots, p-1$, correspond to the required adjustments to absolute flow values from time $k-1$, and are bounded by $\underline{\Delta u}_i = -10$ kg/s, $\underline{\Delta u}_i = 10$ kg/s. The absolute value of flows u_i are also bounded with $\underline{u}_i = -5$ kg/s, $\overline{u}_i = 55$ kg/s, and correspond to adaptations from a nominal value of 65 kg/s for all compressors.

Once a solution to the tracking problem is obtained, the first step of the solution for the intended compressor flow set points is extracted as $\dot{m}_i^{\text{tracking}}$ with their sum representing the necessary control effort. We then solve:

[1] Data available on request from the corresponding author

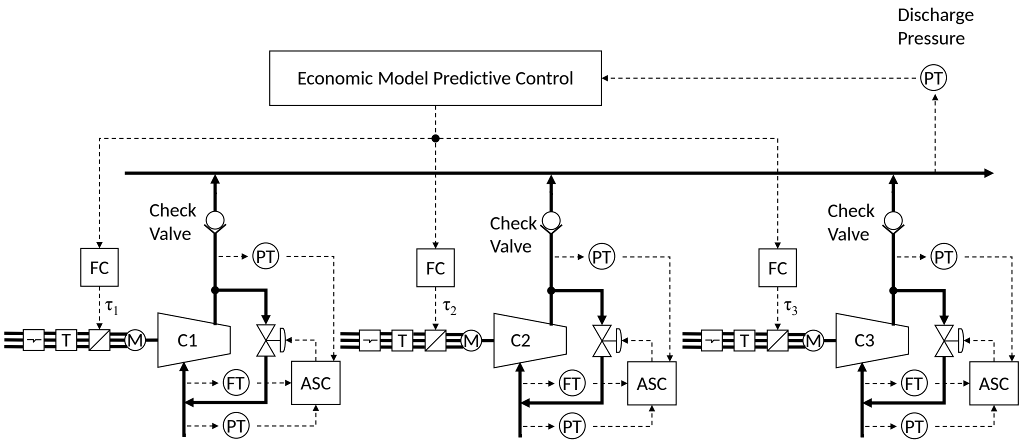

Fig. 4. Implementation of the eMPC approach on the compressor station (adapted from SIEMENS (2012))

$$
\begin{aligned}
\min_{\dot{m}_1,\dot{m}_2,\dot{m}_3} \quad & \sum_{i=1}^{3} P_i(\dot{m}_i) \\
\text{subject to} \quad & \sum_{i=1}^{3} \dot{m}_i = \sum_{i=1}^{3} \dot{m}_i^{\text{tracking}} \\
& \underline{\dot{m}}_i \leq \dot{m}_i \leq \overline{\dot{m}}_i, \quad i = 1,2,3
\end{aligned}
\tag{11}
$$

where the nominal power consumption characteristics P_i are used. Since the compressor flow set points are determined now by redistributing the control actions in an efficiency-aware way, there is no need to consider a further stochastic treatment of power consumption.

Furthermore with eMPC there is no need to provide a nominally optimal operating point for the compressor FCs and a nominal total flow target is not necessary for operation. eMPC also replaces the master controller for station discharge header pressure. The implementation of the eMPC solution is depicted in Fig.4.

3. COMPARISON AND DISCUSSION

3.1 Comparison

The compressor station with the two controllers described in Section 2 is evaluated in MATLAB/Simulink 2024a. The compressors are modeled using performance curves and differential equations representing pressure and flow dynamics (Milosavljevic et al., 2020). Lower level ASC and FC loops are created for all compressors. A discharge header pressure model is created with a baseline gas demand and a superposed random demand fluctuation following a normal distribution with $\sigma = 30\,\text{kg/s}$.

Three different case studies are analysed: nominal RTO coupled with a master pressure controller from (4), stochastic RTO coupled with a master pressure controller from Section 2.3, and an eMPC from Section 2.3.4, following the same arrangements as in Fig.1 and Fig.4. The RTO formulations were executed with a sampling rate of 250 s and the eMPC is executed with a sampling rate of 10

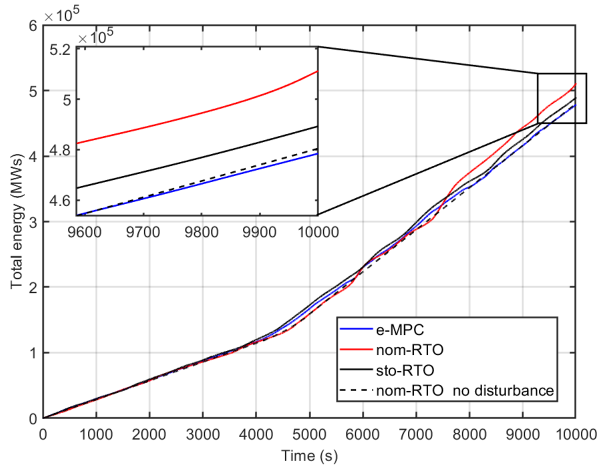

Fig. 5. Evolution of cumulative energy consumption of the station during simulation

s. The simulations are run for 10 000 s with a gas demand change at 4 000 s into the simulation. One simulation using the nominal RTO configuration is run without any demand fluctuations to establish a baseline performance for energy efficiency.

Simulation results for total station gas flow and the discharge header pressure show that all evaluated control and optimization approaches are able to meet operational targets. The main results of the study is shown in Fig. 5. Here we see the gradual build up of the differences in energy consumption when using different algorithms, while providing the same or comparable service by the compressor station. These results are further summarized in Table1.

3.2 Discussion

The gas flows in the simulation scenario are chosen to highlight the sensitivity of optimal load sharing to disturbances in different operating regions. At lower station loads, compressor efficiencies remain stable, making the nominally optimal solution robust against flow variations. However, at higher loads, this solution becomes more fragile and, on average, consumes more energy. In contrast, stochastic optimization distributes the load more effectively across compressors, reducing sensitivity to disturbances and lowering total energy consumption. The eMPC solution performs best but requires solving a more complex optimization problem. It can take advantage of disturbances to improve efficiency but may also use more energy at certain times, depending on the disturbance sequence. The case study was designed to include a compressor with highly sensitive efficiency characteristics, operating in a region where stochastic optimization offers the greatest benefits. The results confirm these expectations, illustrating that real compressor stations, which often operate under comparable conditions, could achieve meaningful energy savings by adopting these strategies, even if only partially.

Table 1. Energy and power consumption comparison across algorithms

Algorithm \ Indicator	Energy (MWh)	Avg Power (MW)
nominal RTO	142	51.12
stochastic RTO	135.91	48.93
eMPC	132.92	47.85
nominal RTO, no dist.	133.47	48.05

4. CONCLUSION

The purpose of this work was to investigate the benefits of using stochastic methods for compressor load-sharing optimization under flow disturbances and to evaluate how eMPC performs as an alternative to a stochastic RTO formulation. The stochastic optimization method, leveraging Gaussian Process surrogates, achieved a 4.3% reduction in energy consumption compared to the deterministic baseline by explicitly accounting for flow variability. The eMPC approach further reduced energy consumption by 2.2%, demonstrating the ability to adapt to and exploit flow disturbances. These results highlight the benefits of incorporating uncertainties into optimization and control strategies for compressor stations.

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