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REDUCING OVERSHOOT IN PROCESS CONTROL FOR EFFICIENT RECOVERY OF NATURAL GAS LIQUID (NGL) USING MODEL PREDICTIVE CONTROL SCHEME (MPC)

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Abstract: *This presents a methodological approach at reducing overshoot in process control for efficient recovery of Natural Gas Liquid (NGL), using the MPC scheme. Reducing process variability to achieve energy-efficient recovery of NGL requires a robust control system. Process variables such as overshoot, rise time, settling time, steady-state error, etc., are controlled to improve system stability, speed of response and prevent mechanical oscillations in control systems. Here, the control problem was formulated in state space, in which a quadratic cost function was used. Kalman filter was used for state estimation with all information necessary to predict future plant behavior. The quadratic cost function was achieved using a genetic algorithm to obtain the optimal control signal. The control system was modeled and implemented in Simulink. A simulation was carried out using the proposed scheme and Proportional Integral Derivative (PID) controller to determine improvement. Results showed that the adaptive MPC scheme outperformed the PID controller at set point following and also, the MPC controller achieved an average of 46.31% overshoot than the PID controller in the reduction of variability in inlet gas flow to the turbo expander.*

Keywords: Cost Function, Flow rate, Genetic algorithm, Kalman filter, Open loop control, Turbo expander.

1. Introduction

Natural Gas Liquid (NGL) is made up of several hydrocarbon products which are produced along with methane (sometimes called "dry" natural gasoline), or as a byproduct of crude oil processing (Ebinger et al, 2013). Methane, propane, butane, isobutene, and produced gas all makeup NGL composition. The growing demand for NGL products resulted in the establishment of turbo expander plants that recover NGL from average gasoline streams by subjecting it to extremely low temperatures - cryogenic temperatures as low as -150oC - 95oC, (Lynch et al, 2007). The purpose of NGL separation and turbo expander system is to cool incoming gas enough to cause propane and heavier hydrocarbons to condense, leaving mainly ethane and methane as the byproduct or residue gas. Cold gas and liquids from the turbo expander and separator are feed into the deethanizer to ensure that the NGL produced is much more stabilized with the extraction of the hydrocarbon light-ends. By cooling the feed gas stream to its dew point temperature, NGL separation is achieved because of the separation of condensed liquid from non-condensed vapor. Low-temperature distillation remains the best means of processing gas combinations, peculiarly when a large inventory of gas stream is involved (Newaz et al, 2010). Low-temperature separations are characterized with the aid of essential interactions between the separation and refrigeration programs.

A turbo expander or an expansion turbine is a centrifugal or axial flow turbine in which gas at very high pressure is suddenly introduced to a large surface area, dropping its pressure rapidly and subsequently low temperature. This process produces a large amount of energy that is also utilized to do other work in the plant-like driving low-pressure compressors (Kerry, 2007; Lynch et al, 2007; Bloch et al, 2001). A turbo-expander is used to refrigerate a stream of gas taking out energy (pressure) quickly from the gas. The center of NGL recovery is the demethanizer subsystem for the recovery of methane from the heavy hydrocarbons, which experts have designed several technologies to handle (Newaz et al, 2010).

The NGL extraction system is complex and non-linear thereby opening improvement opportunities on the conventional control structure known as Proportional-Integral-Derivative (PID) Controllers, which is most commonly deployed. PID controllers mostly have a single Control Variable (CV) and a Single Manipulated Variable (MV). Nonetheless, in a sophisticated operation like the NGL processing, the PID control approach may not be adequate to execute the control strategy needed to satisfy the safety, environmental, and product quality suitable for profitability. Consequently, an improved control technique is required that can adjust the precise setpoints for the CVs and hold the level valves (LVs) within constraint; such that it can gain the desired NGL extraction objectives of maximizing production, reducing energy, and maximizing revenue. Such an improved control system can incorporate all related process variables and use the process models between these variables to predict and hence mitigate the interplay between the variables.

NGLs are frequently processed using a cryogenic turbo expander process (Jibril et al, 2005). The growing demand for NGL products resulted in the establishment of turbo-expander plants that recover NGL from average gasoline streams by subjecting it to extremely low temperatures - cryogenic temperatures as low as -150oC - 95oC, (Lynch et al, 2007).

2. Theory of the Work

Recovery or extraction of NGL can be carried out through several processes, some of which include: J-T effect and cryogenic Turbo Expander (TE), Compression, Cascade Absorption, Ambient Temperature, Absorption, Adsorption, and Straight Refrigeration (Jibril et al, 2005). With technology and the process of cryogenic TE, NGL is usually extracted. From existing research, a survey shows that the TE process has several advantages over other known methodology for NGL extraction. Moreover, when the process of TE is combined with J-T valve and external refrigeration, there is a positive effect obtained from the combination like improved NGL recovery and significant energy efficiency. This conclusion was cited by the report of Jibril et al, (2005).

2.1 Model Predictive Control

Several modeling techniques exist and have been deployed in controlling highly complex and dynamic systems. The one proven to have been successfully deployed is the Model Predictive Control (MPC); which is an advanced process control (APC) technique. Culling from the definition of Lee and Marcus (1967) – MPC is one approach for acquiring a feedback controller synthesis from the knowledge of open-loop controllers. It measures the current process state and afterward computes very swiftly the open-loop control function. The first component to this function is then used for the duration of a short interval, after which a new value of the function is computed for this measurement. In a very natural way, the MPC can be deployed to compensate for measured disturbances and can be applied to plants with multiple variables that must be controlled. Its application can be extended to compensate for intrinsic dead time and in measured disturbance and feed-forward control applications (Guzman et al, 2005).

Dynamic optimization for the analysis and control of cryogenic extraction processes was recommended by Rodrignez et al., (2009). In their approach, they proposed the use of differential-algebraic equation (DAE) model, as the optimal control solution, formulated as single nonlinear programming (NLP) problem approach. In particular, the DAE is a set of algebraic equations over predetermined elements in time, often using implicit Runge-Kutta (IRIC) methods, such as the orthogonal gathering of predetermined elements. Though the proposed technique has the benefit of low Central Processing Unit (CPU) memory usage while processing the control algorithm, it does not allow for more than two optimization variables (Turbo Expander pressure and flow rate fraction, derived through a bypass in cryogenic heat exchangers). However, the proposed Technique has the shortcoming that the offset between NGL recovery and setpoint value is not minimized and the achieved NGL increases at the cost of more energy requirement for the cryogenic process.

The optimization of a turbo expander driven NGL plant by the use of an improved genetic algorithm was proposed by Jang et al., (2005). Three variables were selected for control namely: operation of the flash drum, the output pressure of the turbo expander, and top pressure of the distillation column. The objective of the proposed control technique was to select the ideal pressure spread for effective NGL extraction. Though the process control technique has the benefit of a good process disturbance offsetting results, but it also has the short-comings of increased compression cost due to inefficient power usage.

Working on a technique for optimum design of process control system for integrated NGL recovery plant Mehrproya et al, (2006), pursued the technique through a variable population size genetic algorithm. Their control approach used flow rate, pressure, and temperature of the process fluid stream, to control the turbo expander pressure. The result obtained showed a reduction compared to the conventional PID control loop. There was also a reduction in the turbo expander energy requirement. However, the control structure results in unstable interfaces between the control loops that deploy the three control variables. This makes the tuning of multiple loop control much more difficult than in a PID control scenario.

Optimization by response surface methodology was undertaken by Sanggyu et al., (2012). The natural gas liquid recovery process employs space and energy-efficient dividing wall columns for the integration of depropanization and debutanization, thereby achieving cost reduction in energy usage. However, inadequate optimization of operating conditions such as combining liquefaction and fractionation processes (multivariable control) needs to be adequately realized. Working on increasing the energy efficiency in the NGL recovery process, Xin et al., (2006) approached it with the technique based on quadratic programming. J.T valve position, inlet pressure, and process temperature were used as control variables. The computation experienced fast convergence. The proposed technique realized a good setpoint following as selected for the process pressure; however incremental gas compression required, caused turbo expander revolution per minute (RPM) overdrive and much energy losses.

Croatam, (2010) proposed a Quantitative Feedback Theory (QFT) methodology to provide robust control in the NGL recovery process based on the turbo expander process. Evaluation conducted showed the proposed scheme outperformed the PID controller in terms of set point following and settling time. However, energy usage for the process increased disproportionately with the gas feed rate at a value greater than that of the PID controller. Vinode et al., (2009) proposed the use of Mixed-Integer Nonlinear Programming (MINLP) for the control of turbo expander-based natural gas processing plants. The specifications of the controller included plant component operational construction. The proposed scheme handled different control setpoints for the evaluation of closed-loop performance. Limitations are large variability in the turbo expander inlet gas conditions and the decrease in the process isentropic efficiency with time.

While studying a process control scheme for natural gas processing based on a quadratic search algorithm, Gunzalo et al., (2005) used an algorithm stemmed from classical binary search. In the solver, given the likelihood of each element being the one searched, the objective is to compute a search strategy that minimizes the expected number of

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comparisons. The problem is that the algorithm does not converge quickly. This is due to the variability of the search space. This makes it not ideal for real-time process control. It has a poor set point following for the control of process pressure and gas flow rate. Furthermore, higher variability was experienced with turbo expander RPM in comparison with a mixed-integer nonlinear programming control algorithm. To improve on the existing NGL recovery process, the shortcomings of the process control schemes reviewed have to be addressed. Hence in this study, the Model Predictive Control scheme is proposed to address turbo expander RPM overdrive that leads to energy losses and reduced isentropic efficiency, the variability of process conditions, and the poor controller setpoint-following.

3. Methodology

This work uses operating historic data from an existing NGL extraction plant at an offshore location. The plant is interwoven in a vast network of gas optimization effort that is conceived to reduce/eliminate gas flaring, conserve the ozone layer and give the industrial space more economic gains in the Nigerian Oil and Gas sector. The system as vast as it is, considered the need for efficiency and is currently deployed with a control system that is fit for purpose. However, with this study, deployment of the Model Predictive Control (MPC) scheme - a robust control system for the advanced recovery of NGL, will significantly improve the process currently in use. The control problem was formulated in state space, in which a quadratic cost function was used. Kalman filter (as an Observer), was used for state estimation with all information necessary to predict future plant behavior as shown in Figure 1.

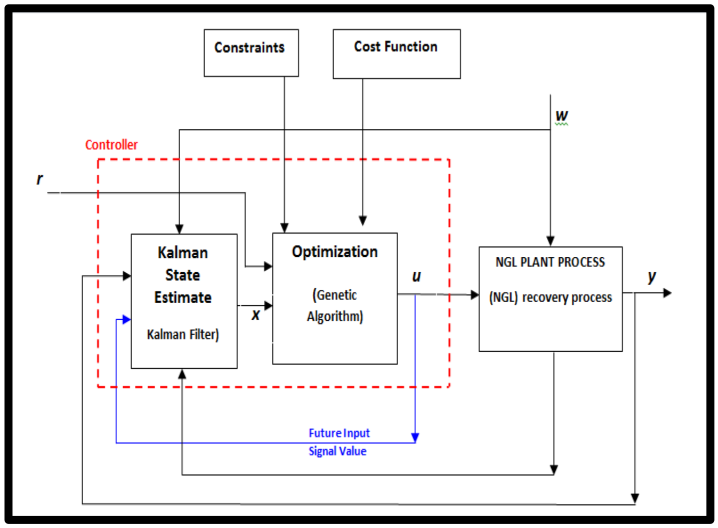

Fig 1: Schematic Representation of the Proposed Control Scheme

To obtain an optimal control signal, the quadratic cost function was achieved using a genetic algorithm. Data for the formulation of control objectives, optimization, constraints, and the objective function for the design of the proposed controller was extracted from process flow and equipment data sheets of the existing process plant.

4. Developing the Genetic Algorithm

To optimize the cost function, the genetic algorithm has to satisfy the constraint of the control. At every given step time "k" the algorithm executes the following pattern of tasks:

i. Utilize the adopted model (i.e. the process model) to cross-check the output of the system.
ii. Apply genetic algorithm optimization to identify the ideal control moves required for the cost function that will satisfy the control constraints. This was achieved as follows:
    a. Create the set of an arbitrary set of potential control moves.
    b. Use the identified process model to match and extract equivalent process output

commensurate with all possible control moves.

c. Check the fit-for-purpose of each solution by applying the cost-function and process constraints.
d. Deploy the genetic operator (selection, mating, crossover, and mutation), and obtain a new breed of possible control problem resolutions.
e. Replicate this technique until such a predetermined number to be generated is reached, thereby defining what the ideal control moves are.

iii. Deploy the optimal control moves as generated in step ii, to the process and verify its control impact.

iv. Repeat steps: i to iii for step time: k+1.

5. Modeling and Implementation of the Controller

The controller was modeled and implemented in Simulink. The Simulink model prediction toolbox and the cryogenic toolboxes were used. The digital model of the turbo expander and other components of the NGL recovery process, the thermodynamic equation of state for gaseous materials, and the mathematical model of the heat exchangers, turbines, compressors, valves, turbo expander nozzles, turbo expander turbine wheels, and turbo expander diffuser, in the form of transfer functions, were translated into appropriate Simulink blocks.

The core MPC is applied as a reference governor as depicted in Figure 2. The intended design objective of the controller is to optimize based on the projected path of the future input variable *u(k)*; then predict the performance (output) of the plant in future *y(k)* (Okafor, Eneh and Arinze, 2017). The optimization is executed within a defined time frame, by giving plant data at the beginning of the time frame.

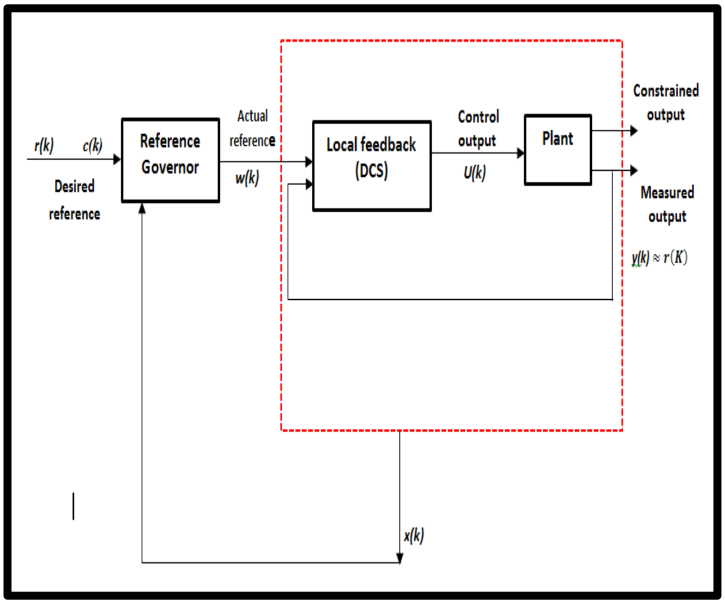

Fig 2: Estimated Plant State + Controller State Expansion of the Controller Structure

The idea of expanding the control structure as in Figure 1 is to apply the MPC as the set-point generator to linear feedback loops of the Distributive Control System (DCS). The DCS is a computerized control system for a complex process or plant having a large number of control loops. In the system, autonomous controllers are distributed in the field, but a central operator-supervisory control oversees them. The DCS increases reliability and reduces installation costs by the localized control functions nearer the process plant. It also gives flexibility for remote monitoring and supervision. Since the proposed process control is an advanced controller, it has to communicate with field devices like sensors, actuators, supervisory control through the DCS. Furthermore, in the likelihood that there is an emergency and an outage of the advanced control occurs, the plant local controller can use the last set-point to continue operation in a reduced or fallback mode (i.e. secure mode).

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5.1 Relationship of the plant, Manipulated Variable (MV), Controlled Variable (CV), and Disturbance Variable (DV)

It is important for the understanding of the design of the control system, that the relationship of the plant, the MV, CV, and DV be put in perspective. Figure 3 shows the relationship between the plants, MV, CV, and DV.

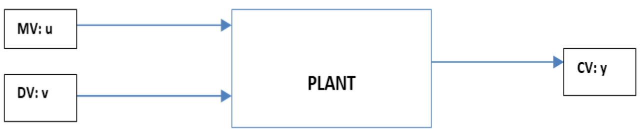

Fig 3: Plant Module and Relationship with (MV), (CV), and (DV)

From Figure 3, CV is the Controlled Variables - y (control output), MV is the Manipulated Variables - u (control input) and DV is the Disturbance Variables - v.

5.2 Control Problem Formulation

This section specifies the formulation of the MPC design problem. The plant model in state space is of the form:

$x(k+1) = Ax(k) + Bu(k): x(0) = x_0$ (1)

$y(k+1) = Cx(k) + Du(k)$ (2)

$u(k) = [u(k|k), u(k+1|k), \ldots, u(k+Nc-2|k), u(k+Nc-1|k)]$ (3)

where $x(k) \in R^n$ is the state vector – belonging to the plane of real numbers at the moment k, $x(k+p|k) \in R^n$ are the predicted state vector for the future time$(k+p)$. The inputs $u(k) \in R^n$ are the manipulated variable (MVs), the output $y(k) \in R^n$ are the controlled variables (CVs). N_c Represents the control horizon (i.e. number of control moves) while the relationship$(k+p|k)$stands for the prediction of the control input value in the future time $(k+p)$ calculated at time k. But to reduce the error that may exist between the predicted controlled output $y(k+p|k)$ and the foreseen set of points: $r(k+p|k)$, the control inputs are calculated in such a way as to minimize the output differences, over the prediction horizon N_p ($p = 1,2 \ldots\ldots, N_p$ being the number of predictions). Then only the first element from the calculated control inputs is applied to the NGL recovery process, being: $u(k) = u(k|k)$. At the next sample time$(k+1)$, there is a new measurement of the process outputs and the whole procedure is repeated.

In every step of this algorithm, the length of the control and prediction horizon is kept the same but is shifted for one value forward (the principle of the receding horizon). In the plant state-space model, A, B, C, D; are the system matrices (the system or plant model parameters). In this work, the system matrices are determined using the process data and the Matlab system identification toolbox. Apart from using the plant's input-output process data, the model represented by Equation 1 - 2, used in the proposed predictive control can be obtained by performing a test on the plant. The test involves injecting known signals, such as steps, multi-sine, pseudo-random, at the plant input and recording the resulting output. A linearized model is then obtained by using the technique of system identification, which ranges from simple curve-fitting to sophisticated statistical-based method.

5.3 Relationship between Equation of States and Space Model of the Plant

As indicated in Figure 4, Equation (1) represents the state-space model of the plant. The output (for example gas flow) from the plant is passed through a flow sensor for measurement. Equation 2 is the representation of the sensor. The measured output y(k) is considered the plant output as given by Equation 2 - the sensor. The control input which is the control sent to the plant, is obtained from the genetic algorithm optimization of the observed system state. The physical sensor and the Kalman filter, constitutes a virtual sensor. The Kalman filter estimates the system state by observing the input and output signals as shown. The genetic algorithm optimization function uses the Kalman filter state estimate (the process) to determine the ideal control moves required for the cost function minimization.

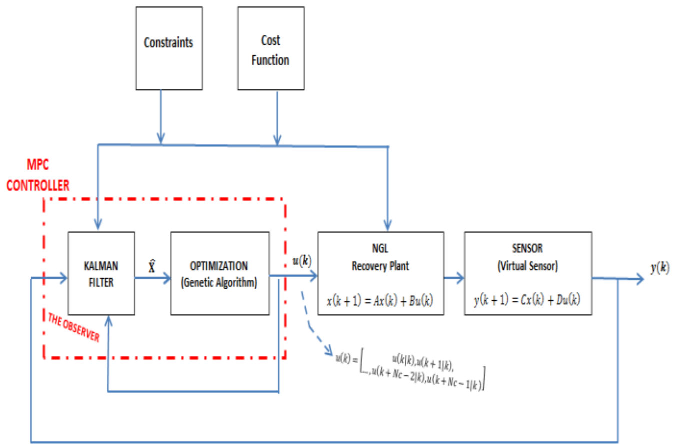

Fig 4: Schematic Representation of the Proposed Control Scheme with State Equations.

5.4 Development of the Digital Model of the NGL Recovery Process

To create the Simulink model of the NGL recovery process, the case study process plant equipment datasheet was used to model the proposed controller and simplified to the based case. The reason is to make for model simplification. However, for model equivalent, the equipment specification and the limits are used in the settings. The datasheet of the case study NGL recovery process was used to create the objective function and the specification of the constraints in the design of the proposed MPC controller. The Industry-Standard Single Stage (ISS) turbo expander process scheme was considered as the base case.

In Kunz and Wagner, (2008) equation of state was used to represent the NGL in the Simulink model. The accurate knowledge of the thermodynamic properties of natural gas and other mixture of natural gas components is of indispensable importance for the basic engineering and performance assessment of the technical process. In this work, the Proportional Integral Derivative (PID) controller was used to benchmark the performance of the proposed model predictive controller for the control of the NGL recovery process. The MPC and the PID controller were integrated into the process model.

6. Simulation and Result

Simulation was carried out to evaluate the performance of the proposed multivariable model predictive controller to control the inlet flow rate to the turbo expander. The dynamic response of the control system in controlling the turbo expander and inlet gas flow rate and pressure was tested against variations in feed gas pressure. The control performance of the proposed MPC controller and that of the PID controller for the control of inlet gas flow to the turbo expander are given in Figures 8 and 9 respectively. The setpoints are 650psi for the lower limit and 1015psi for the upper limit.

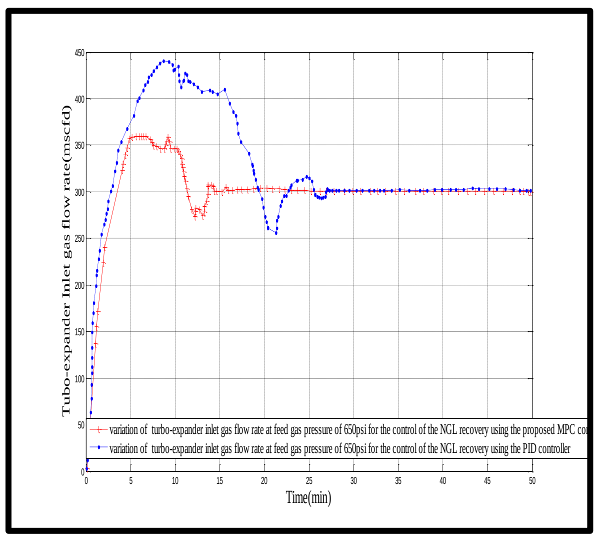

Fig 8: Control of the Turbo Expander Inlet Gas Flow Rate for Gas Feed Pressures of 650psi using the Proposed MPC and the PID Controller

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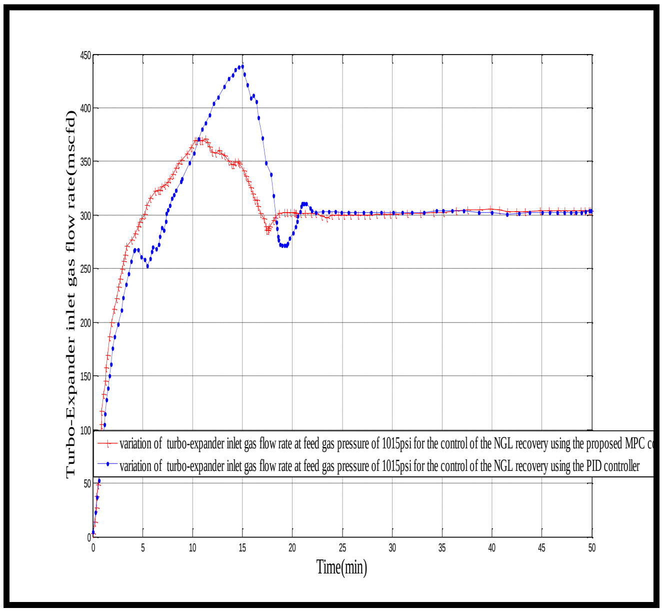

Fig 9: Control of the Turbo-Expander Inlet Gas Flow Rate for Gas Feed Pressures of 1015psi using the Proposed Model Predictive Controller and the PID Controller

From the graphs of Figures 8 and 9, it can be seen that with the PID controller, the process experienced higher overshoots beyond the setpoints, than with the proposed controller. Figure 8 gives the dynamic response of the two controllers to the gas feed pressure of 650psi. From the figure, it can be seen that the PID controller experienced a higher overshoot than the proposed MPC controller at a flow rate control setpoint of 300mscfd. The PID controller caused an overshoot of 142.1415mscfd, whereas the proposed MPC caused an overshoot of 81.893mscfd for feed gas pressure of 650psi. As shown in Figure 9, for feed gas pressure of 1015psi the overshoot caused by the PID controller is 139.6591mscfd. Whereas the overshoot due to the proposed controller is 69. 5285mscfd.This indicates that the proposed genetic algorithm tuned model predictive controller outperformed the PID controller at the set point following. At an inlet pressure of 650psi, the proposed controller caused an overshoot of 42.39% lower than that due to the PID controller. Whereas at an inlet pressure of 1015psi, the overshoot due to the proposed controller is 50.22% lower than that of the PID controller. This represents an average of 46.31% lower overshoot than that of the PID controller.

7. Conclusion

The proposed model predictive control with genetic algorithm optimization for the optimal control of the NGL recovery process was successfully carried out. In this technique, the next move is predicted in advance and subsequently refined using the Kalman filter. The technique enables multivariable to be used to construct robust control laws. The model of the control cost function, the control variable, the equipment design variable, and the control constraints were extracted from the NGL process flow of equipment datasheet of the case study NGL process plant. A simulation was carried out in Simulink and the performance of the proposed MPC controller was compared with that of the PID controller. Results showed that the proposed genetic-algorithm-tuned MPC, outperformed the PID controller at set point following. Also, the MPC controller achieved an average of 46.31% lower overshoot than the PID controller in the reduction of variability in inlet gas flow to the turbo expander. The lower overshoot achieved implies that the system can attain a faster settling time and reduced mechanical oscillations.

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