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SCHOLARLY ARTICLE

Investigating the Effects of Isentropic Efficiency on a Turbo-Expander for Optimal Extraction of Natural Gas Liquid Using Model Predictive Controller

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ABSTRACT

Optimal control of a turbo-expander is paramount for high isentropic efficiency such that the desired higher output in NGL extraction is achieved. In this work, the process flow was implemented in two instances using MPC and PID control systems. In both instances, the operation process variables' data of the turbo-expander from the Mobil Producing Nigeria NGL extraction plant known as GX-facility were used. Mathematical functions for computing the cost function, defining the constraints, input, and state estimation were used as subsystem blocks in Simulink and wired with other process components such as the heat exchangers, sensors, transfer-function blocks and compressor sub-systems to form the NGL extraction plant. A simulation was performed in five locations at intervals of 5sec using the MPC and the PID control systems at 650psi and 1015psi for the lower and upper limits pressures respectively. A baseline of 300mscfd steady-state flow rate was used. The performances of the controllers were evaluated based on the isentropic efficiency achieved for the extraction process. The simulation result showed that average isentropic efficiencies of 43% and 76% were achieved for the PID and the MPC control systems respectively, as the pressure ratio increases. The result indicates that the PID controller greatly degraded with an increase in pressure ratio, while the MPC system experienced much slight decrease.

Keywords: *Isentropic efficiency; Model Predictive Control (MPC); Natural Gas Liquid (NGL); Turbo-expander*

Introduction

Natural Gas Liquid (NGL) is made up of several hydrocarbon products which are produced along with methane or as a byproduct of crude oil processing. Methane, propane, butane, isobutene, and produced gas all make up NGL composition. The growing demand for NGL products resulted in the establishment of an oil and gas process plant (turbo-expander) that recovers NGL from average gasoline streams by subjecting it to extremely low temperatures - cryogenic temperatures as low as $-150℃ - 95℃$ (Onah et al., 2021). Turbo-expander 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). Turbo-expanders are 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 heavy hydrocarbons, which experts have designed several technologies to handle (Newaz et al, 2010).

A typical turbo-expander is characterized by nonlinearities such as overshoot, deadzone etc., and may not be optimally controlled using conventional controllers like Proportional Integral Derivative (PID) system. For optimal extraction of NGL, high isentropic efficiency is paramount. Isentropic efficiency simply compares the actual performance of a steady-flow device (turbo-expander) and the performance that would be achieved under idealized situations for the same inlet state and the same exit pressure. It can be determined by measuring the actual work output of the turbo-expander and by calculating the isentropic work output for the measured inlet conditions and the exit pressure. To achieve high performance and improve the high isentropic efficiency of the extraction system, a robust and adaptive controller such as the Model Predictive Control (MPC) system that is capable of handling the nonlinear characteristics of the turbo-expander system is needed. Model Predictive Control (MPC) system is one of the Artificial Neural Network (ANN) control architectures deployed in the improvement of components of process flow plants especially, the turbo-expander control variables to maintain the stability of the system for optimal extraction of natural gas liquid (Onah et al., 2021).

Literature Survey

A sophisticated operation like the NGL processing needs an adequate control approach to execute the control strategy needed to satisfy the safety, environmental, and product quality suitable for profitability. Consequently, an improved control technique is required to adjust precise setpoints within constraints such that the desired NGL extraction objectives of maximizing production, reducing energy, and maximizing revenue are achieved. In (Jiří, 2018) isentropic efficiency calculation problem was solved by deploying some approximate procedures. The methods described in the work exactly solved the problem of calculation of the isentropic efficiency for various input parameters. In a situation where efficiency is equal to zero, the above-described procedures are suitable for the calculation of the isentropic process but, some of the approximate procedures can lead to inaccurate results.

Thamir and Rahman (2015) developed a simulation model for several configurations of the Combined Cycle Gas Turbine (CCGT) cycle and these were assessed with the influence of the isentropic compressor and turbine efficiency. The performance codes were developed based on MATLAB code. Multi-configured parameters were designed to obtain maximum thermal efficiency and power generation. With the CCGT and higher isentropic turbine efficiency, the maximum overall efficiency was about 58.3%. The proposed CCGT system improved the thermal efficiency by 1.6% and the power output by 11.2%, showing that the isentropic efficiencies and CCGT configurations have a strong influence on the overall performance of the CCGT.

Also in Thamir and Rahman (2015), the effects of the isentropic compressor and turbine efficiency were considered, which allows the selection of the optimum gas turbine (GT) configuration for the optimum performance of a GT power plant. The computational model was developed utilizing MATLAB software. The simulated results show that when considering the effects of the isentropic compressor and turbine efficiency, the reheat GT configuration has higher power output, whereas the regenerative GT configuration has higher thermal efficiency. The maximum thermal efficiency of 52.4% and the maximum power output of 268 MW are obtained with isentropic turbine efficiency. The results show that isentropic compressor and turbine efficiency influence the performance of GTs significantly.

Jiachi et al. (2021) carried out a comparative study on four indexes, namely, symmetric mean absolute percentage error (SMAPE), mean absolute percentage error (MAPE), root mean square error (RMSE), and similarity (SIM) values are utilized to evaluate the forecasting accuracy. Results indicated that the Adaptive Neuro-Fuzzy Inference System (ANFIS) method has a better forecasting effect than Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR) and Nonlinear Autoregression Neural Network (NARNN) for this F-class heavy-duty gas turbine. Through the ANFIS method, the SIM is up to 96.77%, the SMAPE and MAPE are less than 0.1, and the RMSE is only 0.1157. The work suggested that the ANFIS method is suitable for forecasting the isentropic efficiency of this F-class heavy-duty gas turbine compressor. This work tends to use a model predictive control scheme for optimal extraction of NGL by improving the isentropic efficiency of the turbo-expander.

Theory of Work

The cost function used for the MPC optimization computation is the quadratic cost function, given as (Alberto et al, 2004):

$$(JK) = = \sum_{P=1}^{N_p} \|y(k+p|k) - r(k+p|k)\|_Q^2 + \sum_{P=1}^{N_p} \|\Delta u(k+p|k)\|_R^2 \qquad (1)$$

Where;

$\Delta u(k+p|k) = u(k+p|k) - u(k+p|k-1)$; Q and R are two tunable matrix weights.

The relationship intends to minimize the potential errors at the output as well as restrain the fluctuations of the control values within minimal variation. The control horizon must satisfy the constraints $0 < Nc \leq Np$. To obtain a reduced solution to problem solving which will lead to a smaller computational load, it is assumed that Nc<Np.

Constraint Specification

GirishChowdhary, et al, (2014) presented that formulation of constraints can be done for the input and the given states given the MPC control environment. Such input constraints commonly arise from the result of actuator design limits, such as torque saturation in direct current (DC) motors, flow saturation in valves, etc. (Menk Canon 2016). Constraints of input variables (XionglinLuo, et al, 2014):

$$U_{min} \leq U(K) \leq U_{max} \qquad (2)$$

Constraints for high and low limits:

$$U_L \leq U(K) \leq U_H \; (3)$$

Constraints are classified as either hard or soft. Hard constraints must always be satisfied, and if this is not possible the problem is infeasible. On the other hand, soft constraints may be violated if necessary to avoid infeasibility. This work considers only hard constraints.

Control Framework

The MPC system utilizes the behavior of the acceptable process and its parameters to predict and optimize the behavior of a new controlled system, according to some cost function. Here, the representation for the control inputs calculated for time *K* by the MPC controller is given as (Qin and Badgwell, 2003):

$$U(k) = \left[U_{eigt}(k) U_{eigp}(k)\ U_{bcogf}(k) U_{bcdp}(k) U_{csot}(k) U_{exigfr}(k)\right]^T (4)$$

The controller consists of the Kalman filter-based state estimate or (the observer) and the genetic algorithm-based optimizer. The observer used in obtaining the estimate of *X(K)* from the output is given by:

$$Y(k) = \left[X_{eigfr}(k) X_{rgsp}(k)\ X_{egr}(k) X_{jtp}(k) U_{eigtc}(k) U_{lcdp}(k)\right]^T \qquad (5)$$

Then, to enhance the accuracy of the estimated state, the following relationship process disturbance is assumed to be measured:

$W(k) = \left[V_{lrgc}(k)(k)V_{vloc}(k)\right]^T$ (6)

where: $U_{eigt}(k) =$ Turbo expander inlet gas temperature at time k, $U_{eigp}(k) =$Turbo expander inlet gas pressure at time k, $U_{bcogf}(k) =$Booster compressor outlet gas pressure at time k, $U_{bcdp}(k) =$Booster compressor discharge pressure at time k, $U_{csot}(k) =$Cold separator outlet temperature at time k, $U_{exigfr}(k) =$Heat exchanger inlet gas flow rate at time k, $X_{eigfr}(k) =$ Turbo expander inlet gas flow rate at time k, $X_{rgsp}(k) =$ Residual gas function pressure time k, $X_{egr}(k) =$ Turbo expander inlet guide vane position at time k, $X_{stp}(k) =$ JT valve position at time k, $X_{eigtc}(k) =$ Turbo expander inlet gas temperature charge at time k, $X_{lcdp}(k) =$ Level controller differential pressure at time k, $X_{lrgc}(k) =$ Loss of residue gas compression at time k, $V_{vloc}(k) =$ Vibration in tube oil cooler at time k.

Resolution of linear optimization issues are handled using an optimizer, then proffer solution to issues of cost function reduction $J(k)$ - as specified by Equation (1). let it be assumed that the system is described by a discrete state space model:

$X_{k+1} = AX_{(k)} + Bu(k) + Gw_{(k+1)}$ (7)

$y(k) = CX_{(k)} + V_{(k)}$ (8)

Where the noise disturbance W_k and V_k are independent white Gaussian sequences, W_k~N (0, Q) and $V_{(k)}$~N (0, Q).

State Estimation

An observer can conveniently carry out the estimation of the states. This entails estimation of the states by first taking some data upfront and applying a mathematical model to it. This is the basis of what has been described as "virtual sensors". The duo of mathematical model combination with sensors can be viewed as a "virtual sensor" because they are capable of giving information about variables that are not measured directly. The potential to observe the system appropriately determines whether it is possible to estimate the entire system state from observation of the input and output. Figure 1 shows the observer state estimation configuration.

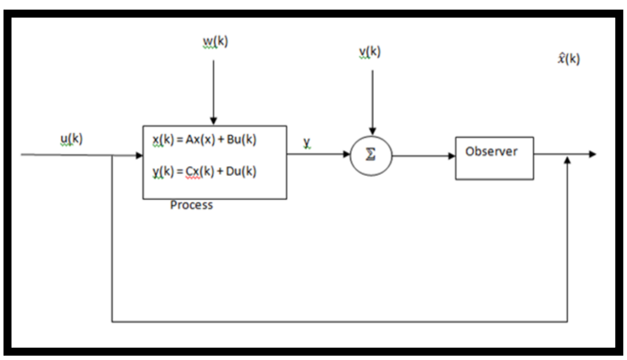

Figure 1: The Control State Observer

Where x(k) is the state at time k;u(k) and the input at time k;y(k) is the measured output. The measurement matrix "C" affects the measured disturbance v(k) - noise realized at the instant *k* is added to the measurement. A state disturbance w(k) is realized at instant "k" before measurement and $\widehat{X}(k)$ represents the state estimate given by the observer.

Implementation

The process flow was implemented in two instances using the MPC system and PID controller. In the first instance, the operation process variables' data of the turbo-expander from the Mobil Producing Nigeria NGL extraction plant known as GX-facility were collected as tabulated in Table 1, to create the objective function and the specification of the constraints in the design of the MPC system.

Table 3.1: Operating Variables of the Mobil Nigeria Turbo-expander

S/N	Process Plant (Turbo-expander) Variables	Value
1	Inlet Gas Temperature	-95.2°F
2	Inlet Gas Flow Rate	Max 302.1 mscfd
3	Inlet Pressure	1012 – 1215 psig
4	RPM of Expander	Max 1420 RPM
5	Compression Power	253 MW
6	Isentropic Efficiency	0.74

The MPC scheme for the advanced recovery of NGL was deployed in the formulation of a control problem in state space, in which a quadratic cost function was used. The Kalman filter as an Observer was used for state estimation, including all information needed to predict the future behavior of the plant. The Observer and process were integrated as shown in Figure 2.

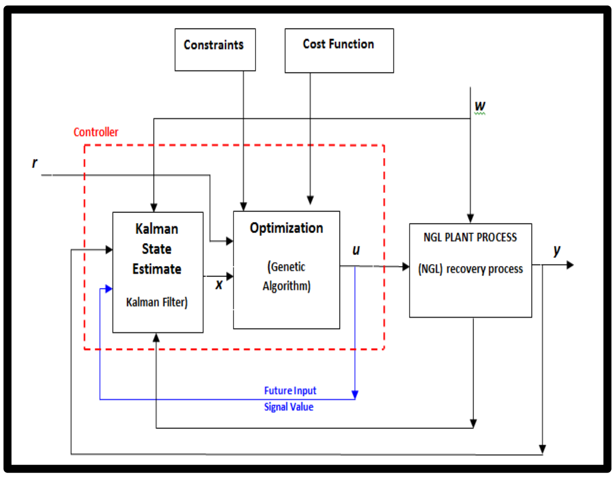

Figure 2: Integration of the Observer and Process (Onah et al. 2021).

The MPC system and the presented equations for computing the cost function, defining the constraints, input, and state estimation were used as subsystem blocks in Simulink and wired with other process components such as the heat exchangers, sensors, transfer-function blocks and compressor sub-systems to form the NGL extraction plant as shown in Figure 3.

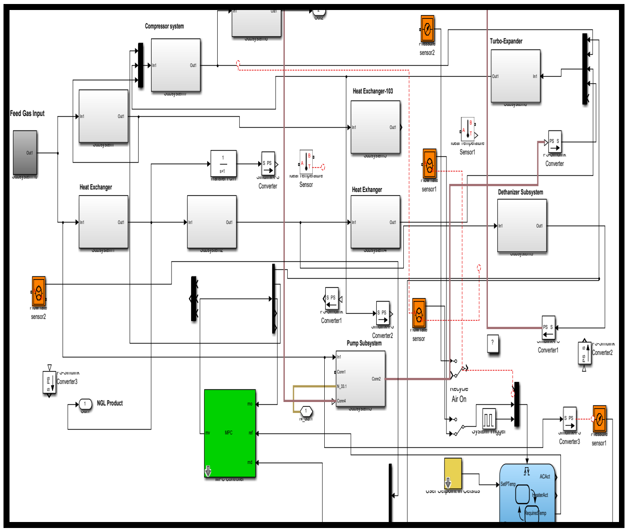

Figure 3:NGL Extraction Process Flow Integrated with the MPC in Simulink

In the second instance, the GX facility was integrated with the PID controller. The PID controller is represented by (Okafor et al., 2020):

$$U(t) = Kp.e(t) + Ki\int_0^t e(\tau)d\tau + Kd\frac{d}{dt}e(t) \qquad (9)$$

where: $U(t)$ is the controller output signal, $e(t)$ is the error signal, Kp is the proportional gain, *Ki* is the integral gain and *Kd* is the derivative gain. Figure 4 shows the implementation of the Simulink Model of the NGL extraction process flow Integrated with the PID Controller.

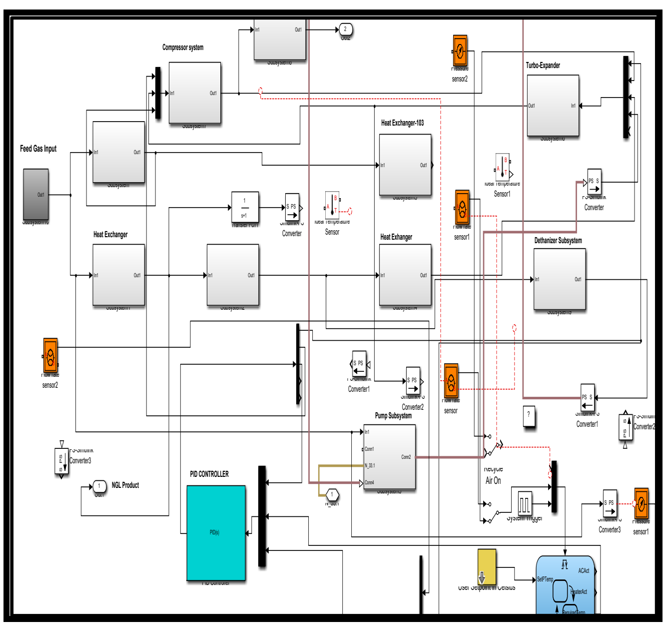

Figure 4: NGL Extraction Process Flow Integrated with the PID Controller in Simulink

Simulation and Result

The simulation was performed using the MPC and the PID control systems at 650psi and 1015psi for the lower and upper limits pressures respectively. A baseline of 300mscfd steady-state flow rate was also used. The simulation was done in five locations at intervals of 5sec. The performances of the controllers were evaluated based on the isentropic efficiency achieved for the extraction process. Readings of isentropic efficiencies from the locations were taken and tabulated in Table 2.

Table 2: Achieved Isentropic Efficiency

Time (min)	Isentropic Efficiency	
	PID	**MPC**
1	0.67	0.91
3	0.58	0.83
5	0.40	0.73
7	0.30	0.69
9	0.22	0.62
Average	**0.43**	**0.76**

From the table, the average isentropic efficiency for the PID and the MPC control systems are 43% and 76% respectively. The MPC system outperformed the PID controller by 43.42%. The result indicates an obvious decrease in the isentropic efficiency of both control systems as the pressure ratio increased. However, the decrease in the isentropic efficiency of the MPC system is not as large as that of the PID controller. While the isentropic efficiency of the PID controller greatly degraded with an increase in pressure ratio, the MPC system experienced much slight decrease as shown in Figure 5.

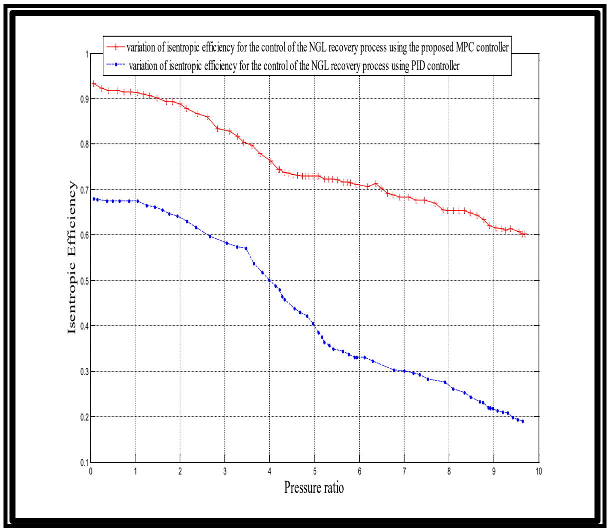

Figure 5: Isentropic Efficiency of the MPC and the PID Controllers.

Furthermore, the MPC system tried to keep isentropic efficiency from going below 0.5. The result signifies that the MPC system almost kept the entropy of the system unchanged and prevented significant loss of energy compared with the PID controller.

Conclusion

Optimal control of a turbo-expander is important in achieving high isentropic efficiency in the extraction of NGL for desired higher output. An increase in the isentropic efficiency effectively decreases the irreversibilities in the turbo-expander and directly increases the desired output. The process controller is very vital in ensuring that the condition of the gas at the inlet of the turbo-expander is within process set points thereby, achieving high isentropic efficiency. Results showed that optimal control of the process flow can be achieved using an adaptive controller such as MPC.

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