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Implementation and Performance Evaluation of a Model Predictive Controller for a Semi-Autogenous Grinding Mill

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ABSTRACT

This paper investigates the implementation of a model-based predictive control (MPC) strategy to improve the performance of a semi-autogenous grinding (SAG) mill in a uranium mineral processing plant. The SAG mill, crucial in crushing and grinding uranium ore to the desired size, is currently managed using conventional proportional-integral-derivative (PID) controllers. However, to enhance production efficiency and control over the SAG mill's variables, this paper suggests the adoption of MPC. The proposed MPC controller is developed using a neural network (NN) model of the SAG mill, created in MATLAB with data collected over 21 days. The effectiveness of the MPC controller is assessed by contrasting its response with that of the real-time operator control. This comparison utilizes tools like MATLAB and the RSlinx remote server for accessing OPC real-time data. Findings reveal that the MPC controller exhibits a quicker reaction to alterations in the SAG mill's process outputs and proficiently regulates crucial outputs such as Mill mass, ensuring that the manipulated variables stay within their designated limits. Unlike operator control, which is slower and adjusts one variable at a time, the MPC approach can maximize the mill's throughput rate without impacting the ore feed rate. This demonstrates the MPC controller's superior ability to optimize SAG mill operations efficiently.

Keywords: model predictive control, semi-autogenous grinding mill, uranium ore processing, neural network modeling and operational efficiency optimization.

INTRODUCTION

A semi-autogenous grinding (SAG) machine is a cylindrical machine used mostly in mineral processing plant for ore size reduction and it is one of the most energy intensive and important operation machine in the mineral processing industry [1]. The SAG mill reduces the large size ore to the required particle size by a tumbling action caused by the rotation of the mill. The tumbling of the ore in the mill encourages the rock-on-rock and rock-on-steel ball grinding. The operation of the SAG mill is governed around the ore feed, mill process water, crushed pebble feed and mill rotation speed as input parameters that are important to the SAG mill operation and grinding efficiency [2]. This input parameters are controlled in order to control the weight of the SAG mill, the power draw and other SAG mill throughput contributing factors. The SAG mill grinding process is a closed-circuit process that is increasingly complex to control effectively and efficiently [3]. The complexity around the SAG mill is due to unmeasured disturbance factors, process delays and the coupling and interaction between process variables.

Different types of SAG mill control methods have been investigated and implemented over the past years [4]. Some of these control strategies include advanced process control (APC), expert control, PID control, and operations manager control. Mineral processing plant mostly have distributed control system (DCS) implemented as primary level control, but these control approaches are not able to run the SAG Mill as designed [5]. A simple proportional-integral-derivative (PID) controller cannot be utilized as a control strategy for the entire process of the SAG mill in order to yield maximized throughput. This is because the input variables interact in a way that is not really clear as to how they affect the mill throughput. The SAG mill control can be optimized to achieve a favorable throughput by implementing a different control strategy. Advance process control methods are seen as the type of approach that can be used to successfully control SAG mill circuits. The application of model-based predictive control (MPC) has been advocated by Yutronic et al. [6], as control for mineral recovery process because MPC are very simple to tune, intuitive and have predictive characteristics that account for disturbances and dead times. The control strategy proposed by Bouchard et al. [7], was that of using a selector-based strategy between the load PID controller and the power PID controller and switches between controller if certain load or power constraints are violated. M. Ruel [8], utilizes Fuzzy logic control as another form of APC that is very ideal in situations when an experienced operator has better control of a process than a PID controller to control the SAG mill circuit. Expect control system (Fuzzy control) that aim to maximize throughput have no clear procedures to tune them and exhibit poor response to disturbances unlike MPC that allows for handling of operational constraints, coupling of process variables and are easy to tune [9]. Model-predictive control is an important and frequently used advance control technique for complex multivariable control problems [10]. MPC and other model-based controller provide a significant advantage over PID when applied to grinding circuit [11].

In order to establish a model-based controller, an accurate or approximate model of the process needs to be obtained first. A model can be obtained either from mathematical modelling or obtained from historical data of the process that can be used to identify the behavior of the system. The model is used as the basis for the design of an MPC controller and it is the vital part of the predictive control implementation. In [12], the process model is obtained by the controller that models the system response using generic function series approximation based on Laguerre polynomials providing a simple mathematical model. Haijie et al. [13], Use a dynamic mathematical model of the SAG mill circuit obtained by interlinking sub process modules within the circuit. The mathematical model obtained are complex and mostly applicable only to that mineral processing plant. Bauer et al. [14], applied an industrial derived mathematical model by Le Roux et al. [15] to explain the concept of advance process control via simulation. A lot of process nowadays are equipped with capabilities of automatic data acquisition stored on historian data servers that collect a large amount of information about a certain process operation [16]. Agarwal et al. [17], applied sophisticated statistical and neural network techniques to the SAG mill data in order to identify the data streams that are important to the process and obtain a SAG mill power consumption model using. Other literatures, such as Yutronic et al. [6], have also utilized historical data to obtain process model. Therefore, sample data collected can be used to study and identify a process model using sophisticated software such a MATLAB system identification toolbox, neural network app as well statistical software to analyze the relationship between the required variable for a process or system.

Problem statement

The control strategy currently employed for SAG. Mill primarily involves basic PID control complemented by manual interventions from operators. This approach, however, has been found to be insufficient in efficiently managing the SAG mill's operations. One of the main issues with this control strategy is its slow responsiveness to measured disturbances like pebble recycle, mill rotation speed etc, and unmeasured disturbances that regularly occur in the mill's operational environment. Due to this lag in response, the SAG mill often experiences suboptimal performance in key operational areas. Specifically, there are noticeable inefficiencies in terms of the mill's throughput: the rate at which the ore is processed and, power consumption. The slow reaction of the control system means that it struggles to quickly adapt to changes or fluctuations in the milling process, which could be caused by variations in ore quality, size, hardness, or other external factors. This inability to swiftly adjust to such disturbances often leads to a reduced rate of processing the ore, resulting in lower throughput. Furthermore, the inefficient control strategy contributes to higher energy consumption. The delay in response to changing conditions means that the mill may operate under less-than-ideal conditions for extended periods, thereby using more power than necessary. This not only increases operational costs but also can lead to additional wear and tear on the mill's components, potentially shortening its lifespan and increasing maintenance requirements. In summary, the current basic PID and operator control strategy for the SAG mill is hampered by its slow response to disturbances in the milling process, leading to decreased efficiency in throughput and increased power consumption, which in turn impacts the overall productivity and cost-effectiveness of the mill's operations.

Aim and objective

The focus of this study is on implementing and evaluating a MPC system for the grinding circuit of a SAG mill. The research aims to assess the effectiveness of MPC in comparison with the current PID. Control method, specifically looking at aspects such as throughput, power usage, and torque stability. The key goals of this research include:

- Gathering and analyzing data related to the input and output variables of the SAG mill.
- Developing a process model using MATLAB's neural network capabilities, based on the collected process data.
- Designing and deploying an MPC controller designed to enhance the throughput efficiency of the SAG mill.
- Conducting a comparative analysis between the performance of the newly implemented MPC controller and the existing manual process control by operators.

METHODOLOGY

MPC control strategy

Figure 1 illustrates the outlined MPC strategy for the SAG mill. In this control scheme, the MPC controller is responsible for managing four key output variables: mill mass (WIT-004), mill power draw (JT-001), mill recycle load (WIT-003) and also mill torque (NIT-001). To effectively control these outputs, the MPC system adjusts four manipulated variables: WIT-001, the setpoint of FIC-001, the setpoint of SC-001, and WIT-002. This approach demonstrates the comprehensive and interactive nature of the proposed MPC strategy in optimizing the SAG mill's operations. The Figure 1 shows the discharge hopper where the fine materials are recovered and pump to other section of the plant. The pebble cone crusher where pebbles from the SAG mill are further reduced in size and return to the SAG mill via the CV-002 conveyor. This study followed a structured methodology, beginning with the collection and analysis of historical process data. After a thorough examination of the sampled data, it was imported into MATLAB for additional processing. In MATLAB, this data was utilized to develop a process model for the SAG mill, leveraging the neural network toolbox. This newly created model was then subject to validation through testing with both the training dataset and various random sets of process input and output data.

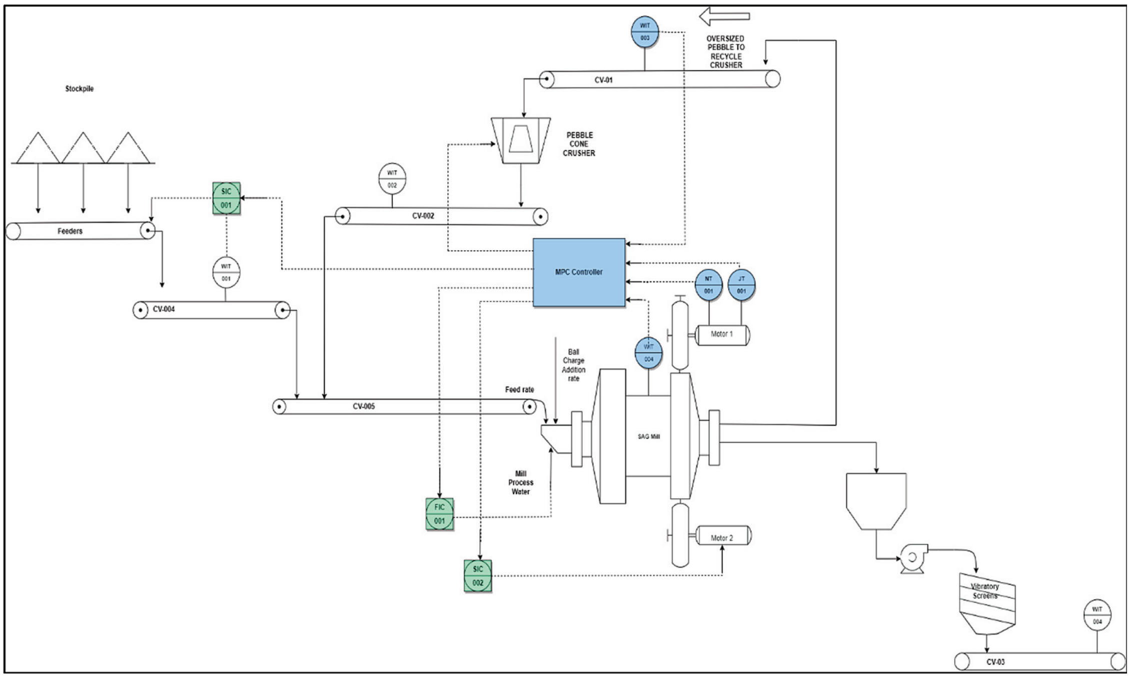


Figure 1. Proposed SAG mill MPC control strategy

Following the successful validation of the SAG mill process model, the next step involved the design of a MPC controller based on this model. The MPC controller was subsequently implemented, and its performance and results were meticulously recorded and analyzed. This process allowed for a comprehensive evaluation of the effectiveness of the MPC controller in managing the SAG mill operations.

Data collection and analysis

A dataset encompassing 21.8 days of operational data from the SAG mill was acquired and subsequently imported into MATLAB for analysis. This dataset was compiled from various operational periods to ensure a comprehensive representation of the SAG mill's performance under diverse conditions. An illustrative sample of the process output data, as captured in this dataset, is presented in Figure 2.

Modelling the SAG mill

Figure 3 presents the neural network's architecture, demonstrating the training process involving four input variables-feed rate, water ratio, pebble recycle, and SAG speed-with their corresponding outputs: mass, power, recycle load, and torque. This training process utilizes a nonlinear input-output method. Additionally, the algorithms employed for the training and performance evaluation, which focus on minimizing the mean squared error (MSE), are detailed in Figure 4.

Model validation

The SAG mill predictive neural network model is discussed here. Figure 5–6 illustrates the finalized predictive neural network model for the SAG mill process, which was rigorously tested using a set of random data.

In this model, the input variable (x) is linked to the four designated process inputs, as indicated in the

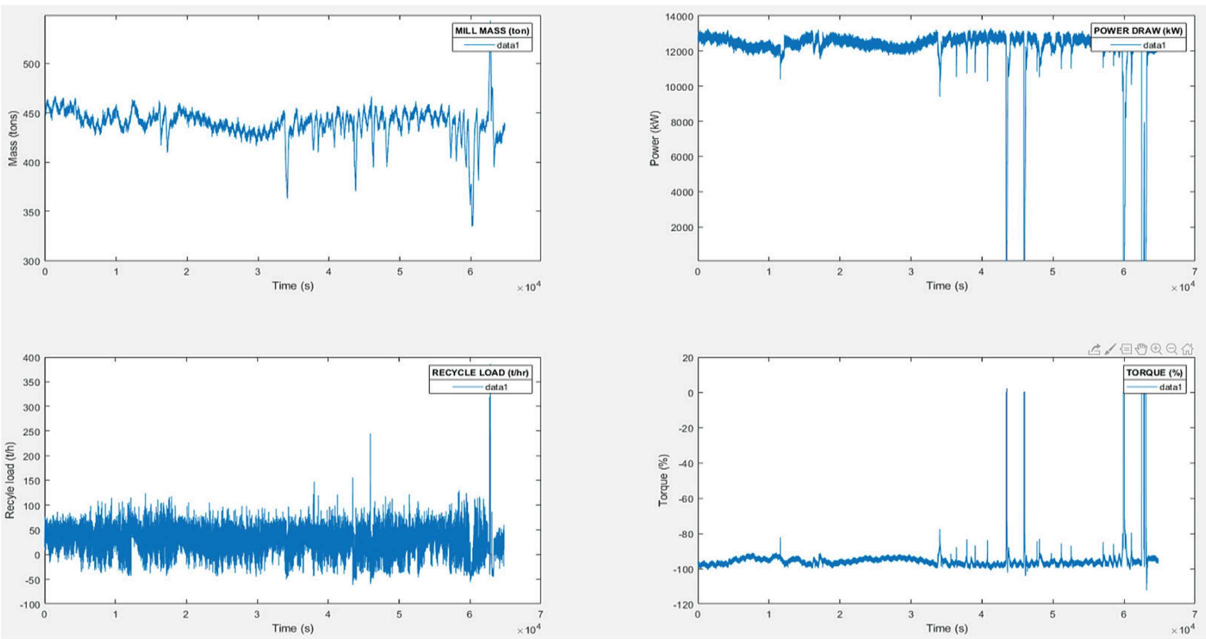


Figure 2. DATA05, process output data sample

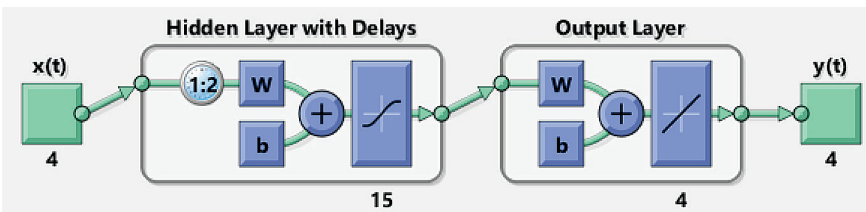


Figure 3. Structure of neural network training

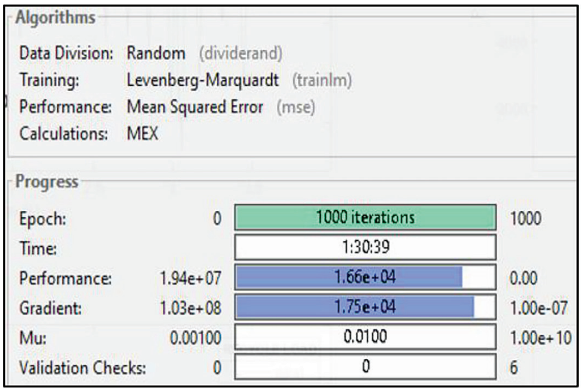


Figure 4. Training algorithm progress

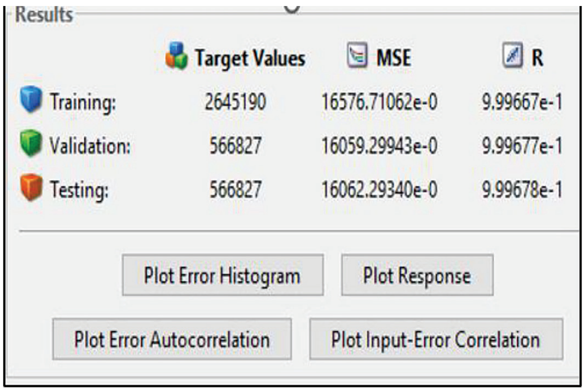


Figure 5. Model testing and validation performance

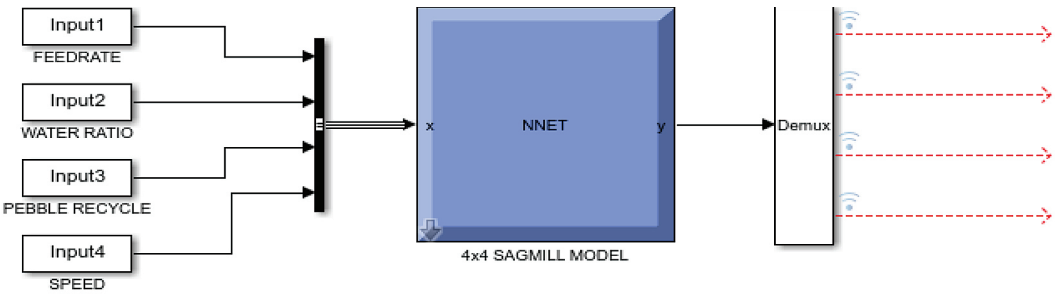


Figure 6. Model of the SAG mill process

diagram. The output from the model is then fed into a demultiplexer block, which separates the combined output signal into four distinct output signals. These discrete output signals are intricately monitored and presented on a Simulink dashboard, where they are subjected to a thorough comparative analysis and artfully superimposed with the real-time process output data. Figure 7 represent the model testing and validation performance which is tested using set of random data and showing the good results.

It showcases a side-by-side evaluation of the predictive neural network model's outputs against the real SAG mill process data. In the upper left portion of Figure 7, the mill mass output from the neural predictive model (represented in orange as Demux1) is aligned with the real mill mass output (in blue, labeled as data mass), demonstrating a significant match between the model's predictions and the actual outputs. Shifting to the upper right graph in Figure 7, the neural predictive model's performance for power draw (Demux2, in orange) is displayed next to the actual power draw data (data power, in blue). The predicted power output from the model closely resembles the actual power draw of the process.

In the lower left graph of Figure 7, the output for the recycle load from the model (Demux3, in orange) is set against the actual process recycle load (data recycle, in blue). This comparison indicates a strong correlation between the neural model's predictions and the actual recycle load data. The lower right graph depicted in Figure 7 showcases the effectiveness of the SAG mill torque predictive model. In this representation, the model's torque predictions (Demux4, depicted in orange) closely align with the actual process torque output (data torque, shown in blue), providing compelling evidence of the model's predictive precision in this specific aspect.

MPC controller design

The development of a MPC controller follows the creation of a process model. This MPC controller is tailored to regulate the model outputs, ensuring they align with predetermined setpoints. The control strategy encompasses the meticulous adjustment of four variables: feed rate, water ratio, pebble recycle, and SAG mill speed. These adjustments are meticulously orchestrated to ensure that the outputs of the predictive model precisely align with their designated target references. Key considerations in the design of the MPC controller include the maintenance of the

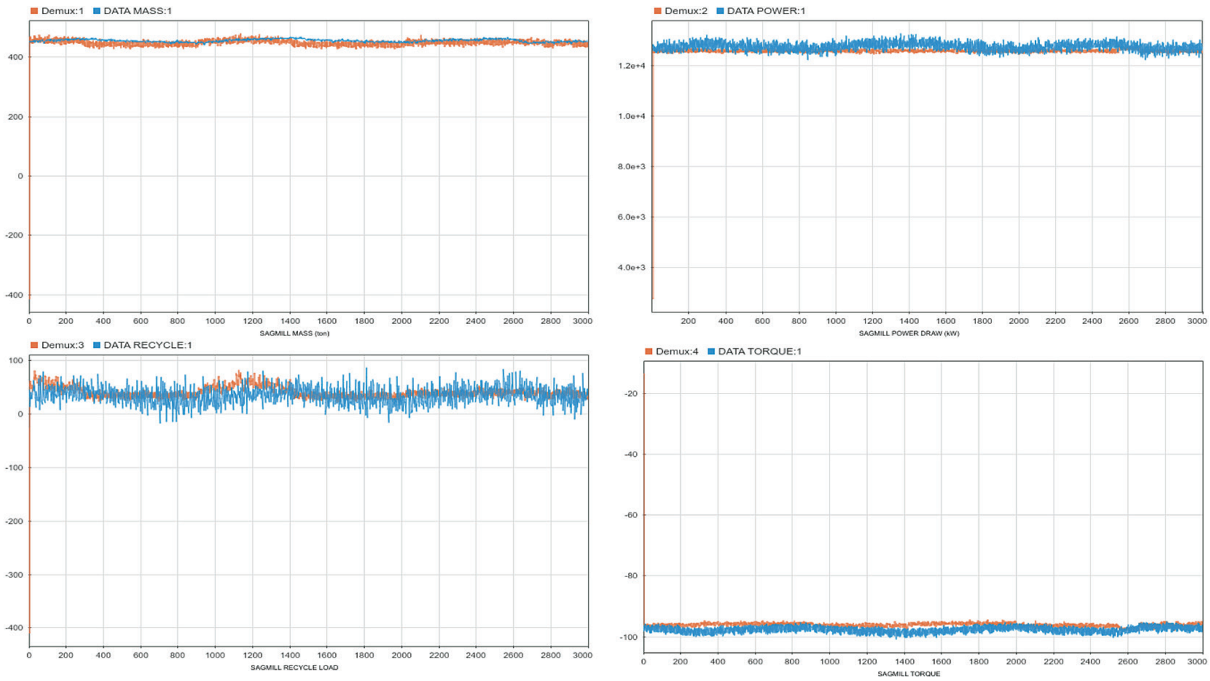


Figure 7. Testing and validation of the model using DATA05

FeedRate to the SAG mill at its maximum or an elevated level, aimed at augmenting and optimizing throughput (Figure 8). Additionally, the precise control of the SAG mill's mass (weight) is of paramount importance to achieve optimal grinding efficiency and maximize mill production.

Defining accurate input and output constraints is vital for effective control. The arrangement in Figure 8 demonstrates this, showcasing the integration of the MPC controller block with the SAG mill model block within the Simulink environment. Moreover, it presents the configuration of the MPC control system as seen in the MATLAB MPC designer tool. This Figure underscores the four manipulated variables and the four measured outputs (MO) of the controller, all of which are based on the neural network trained model of the SAG mill.

Defining the limitations on process measurement outputs

Table 1 outlines the specific output constraints for the SAG mill when it is operating at full capacity. These constraints delineate the upper and lower limits beyond which the SAG mill may encounter

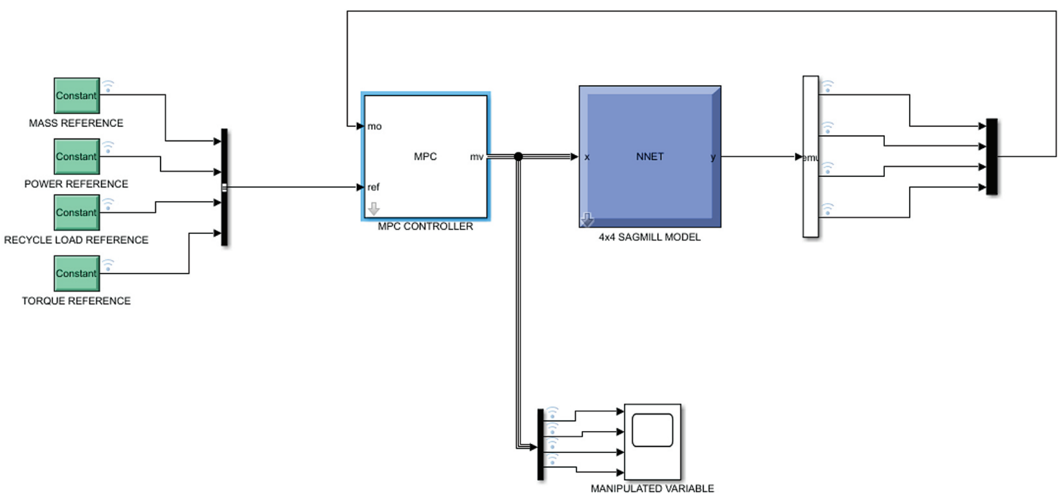


Figure 8. MPC controller design

Table 1: Process measure output constraints

Channel	Type (output)	Min	Max
Mill mass (ton)	MO	400	600
Power draw (kW)	MO	11000	12800
Recycle load (t/h)	MO	10	250
SAG torque	MO	-97	-90

trip conditions. The role of the MPC controller is to consistently maintain the outputs within these defined operational limits to ensure smooth and uninterrupted functioning of the SAG mill.

Table 2 presents the specific ranges and incremental adjustments for the control variables used by the MPC controller. These parameters are carefully set to prevent scenarios such as overfeeding or underfeeding the SAG mill, supplying excessive or insufficient water, and operating the mill at inappropriately high or low speeds. The table serves as a guideline to ensure that the controller optimally manipulates these variables, maintaining the balance and efficiency of the SAG mill's operation. Figure 9 provides a visual representation of the predefined nominal values for both the inputs and outputs within the MPC controller. These values play a pivotal role as fundamental reference points during the intricate design and fine-tuning phases of the controller. They serve as a benchmark, guiding the determination of the optimal control settings required for the system.

Figure 10 illustrates the weights assigned to the manipulated variables (MV) and measured outputs (MO) within the control system. These weights signify the relative importance of each input and output in the control process, guiding the controller in prioritizing its adjustments and responses.

Testing, tune and simulation of the MPC controller

Following a series of tuning trials, the final tuning parameters selected are displayed in Figure 11. These parameters include setting the MPC controller's sample time to 2 seconds, configuring the controller's state estimation to a higher level, and adjusting the controller's performance to be more robust, albeit slightly less aggressive.

Simulation using reference (580 t, 11000 kW, 55 t/h, -90%). Observations indicate that the settling time for the controller's output response has been extended, resulting in a control process that is less erratic and more stable initially before reaching stabilization. It appears that only the mill mass consistently settles and stabilizes at the reference point. This behavior is likely attributed to the specific weight assigned to the mill mass in the controller's settings. As a result, the controller prioritizes stabilizing the mill mass at its setpoint before addressing the other outputs.

Table 2. MV constraints and rate of change

Channel	Type (MV)	Min	Max	Rate min	Rate max
Feed rate (t/h)	MV	800	1800	-10	10
Water ratio (-)	MV	0.3	0.5	-0.001	0.001
Pebble recycle (t/h)	MV	0	250	-10	10
SAG speed (%)	MV	-99	-80	-0.05	0.05

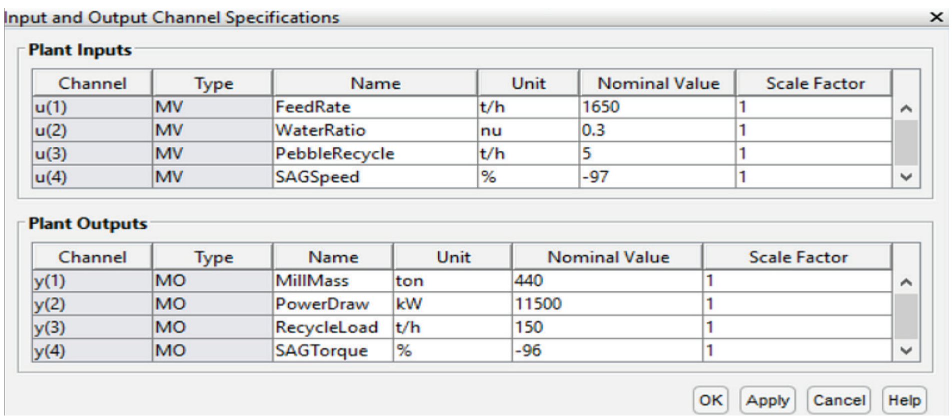
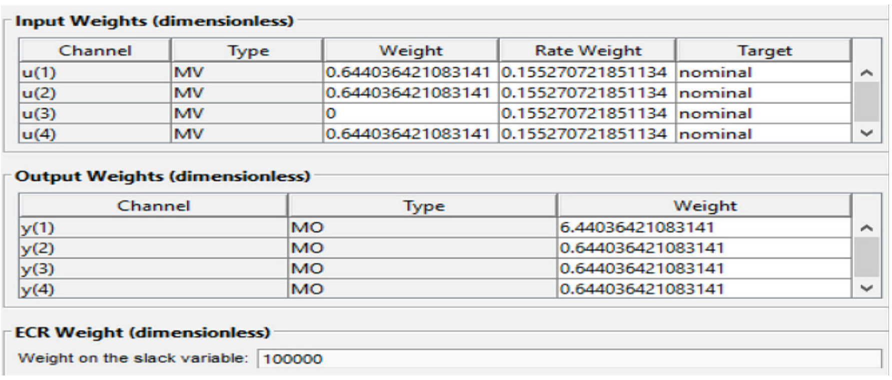


Figure 9. Nominal process I/O values



Input Weights (dimensionless)

Channel	Type	Weight	Rate Weight	Target
u(1)	MV	0.644036421083141	0.155270721851134	nominal
u(2)	MV	0.644036421083141	0.155270721851134	nominal
u(3)	MV	0	0.155270721851134	nominal
u(4)	MV	0.644036421083141	0.155270721851134	nominal

Output Weights (dimensionless)

Channel	Type	Weight
y(1)	MO	6.44036421083141
y(2)	MO	0.644036421083141
y(3)	MO	0.644036421083141
y(4)	MO	0.644036421083141

ECR Weight (dimensionless)

Weight on the slack variable: 100000

Figure 10. Inputs and outputs weights

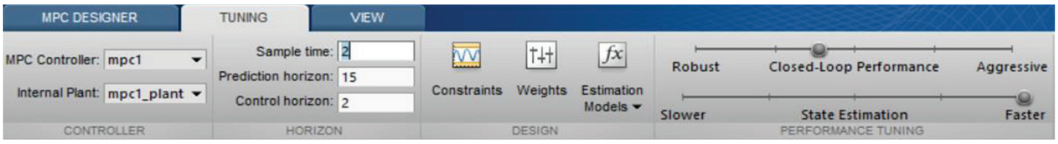


Figure 11. Tuning parameter Hp = 15, Hc = 2 and T = 2s

Figure 12 illustrates the process through which the MPC controller adjusts variables like feed rate, water ratio, pebble recycle load, and SAG mill speed to achieve the output responses depicted in Figure 13. To meet the desired output reference, the controller increases the feed rate, eventually stabilizing it around 1650 tons/hour. Concurrently, there is a gradual reduction in the water ratio, which settles at approximately 0.3. The SAG mill speed is also methodically decreased, eventually stabilizing at around 98% (-98). Additionally, the controller maximizes the pebble recycle rate.

The simulated results of the MPC's manipulated variables, such as those shown in Figure 13, provide valuable insights for comparing the efficiency of operator control with that of the newly designed MPC. This comparison will be crucial in determining which control method not only

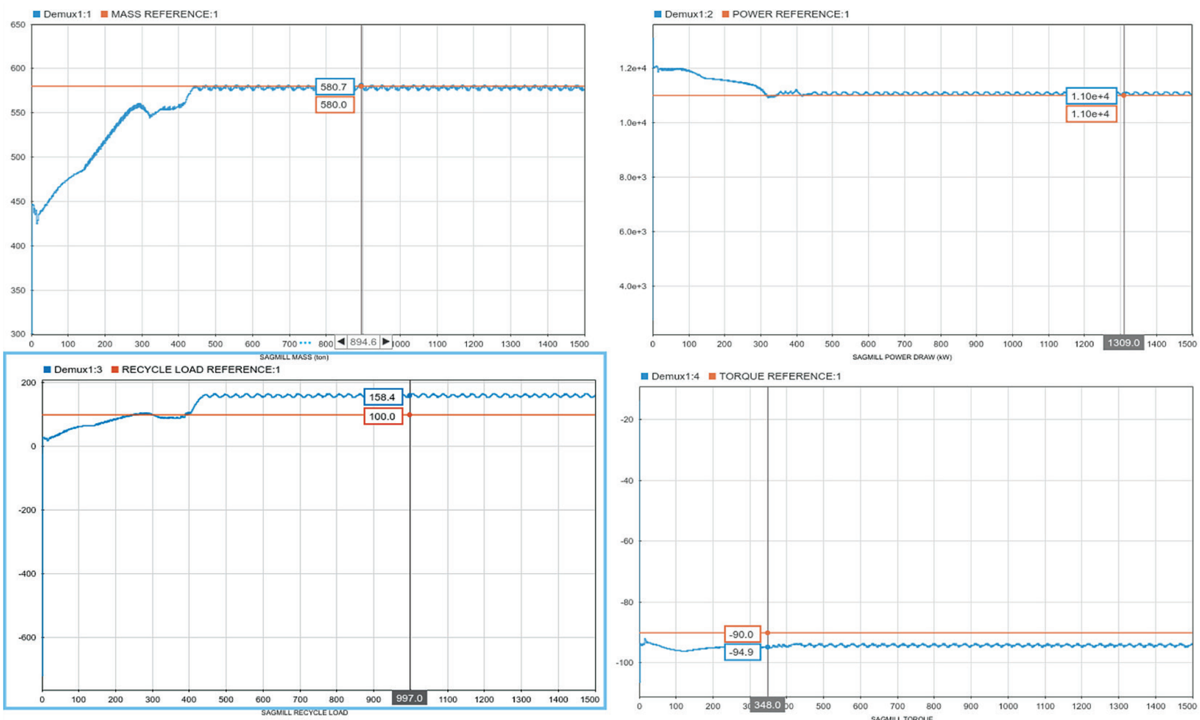


Figure 12. MPC manipulate variable simulation results

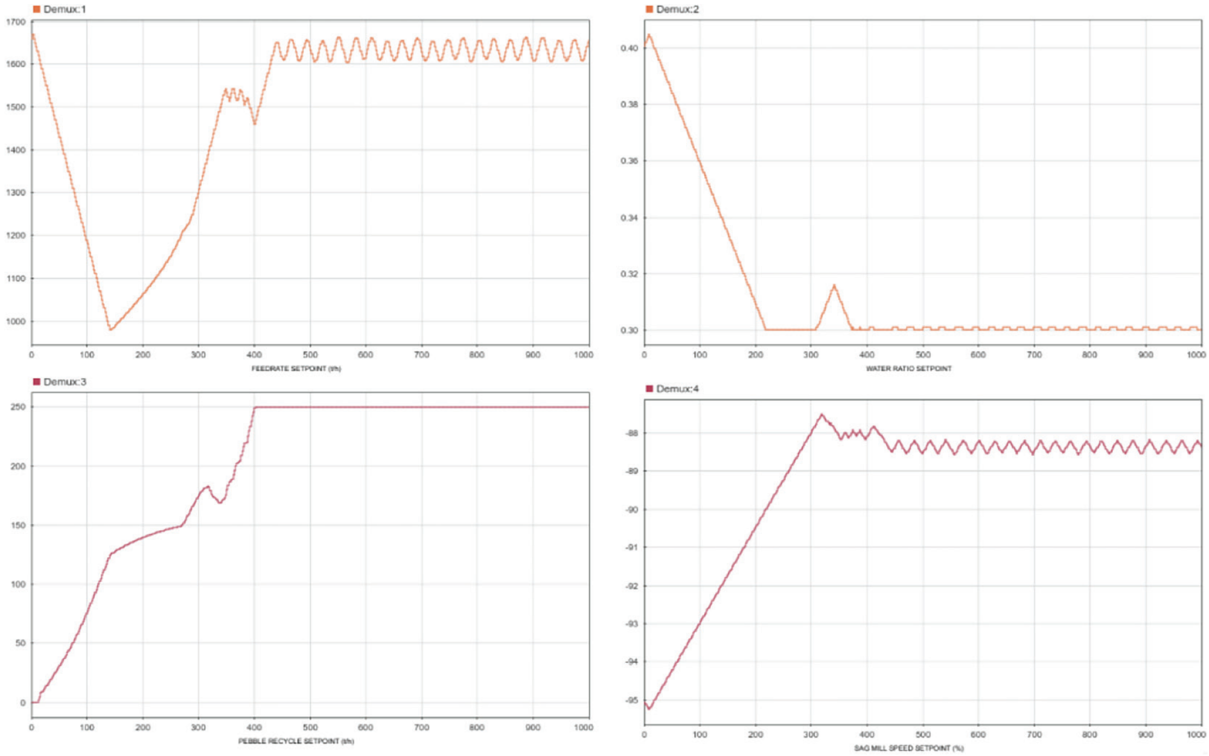


Figure 13. MPC output response, reference [580t, 11000kW, 100t/h, -90%]

offers more effective control but also optimizes SAG mill throughput while conserving energy and water resources.

Implementation of the MPC controller

In this section of the study, we will establish a connection between the measured outputs generated by the MPC controller and the actual process outputs using the MATLAB OPC DA application. This connection will establish communication with the process plant's PLC through the RSLinx Remote server. By contrasting real-time process outputs with the reference setpoints established within the MPC controller, we will have the opportunity to observe and analyze how the MPC controller adapts the manipulated variables when compared to the operator and PID control methods. The data gathered from this implementation will subsequently undergo a comprehensive evaluation to ascertain whether the MPC controller outperforms operator and PID control in terms of optimizing mill throughput and minimizing energy consumption. The above Figure 14 illustrates the practical application of the specially crafted MPC controller, making use of real-time data from the SAG mill for the purposes of this research project. During this implementation phase, the designed controller will be exclusively employed.

RESULTS

Following a 20-minute real-time simulation conducted with specific output references, as illustrated in Figure 15, we closely observed how the actual SAG mill process outputs were manually adjusted to align with these predefined references. Additionally, Figure 16 visually illustrates the contrasting approaches of MPC control and operator control in managing actual process input variables. To provide a comprehensive assessment and presentation of the responses and behaviours exhibited by both MPC control and operator control, as depicted in Figure 15 and Figure 16, we will systematically conduct a comparison and summarize the findings in Table 3.

Table 3 provides a comparative analysis of the responses exhibited by the operator and MPC controls in various scenarios concerning the SAG mill process outputs: At t = 100 seconds, the observed conditions involve mass, power, and torque being below their reference values, while the recycle load exceeds its reference point: operator control predominantly maintains the status quo regarding process input variables, with only a reduction in pebble feed noted. There are minimal alterations in the operator's control actions over the 20-minute simulation period. In contrast, under MPC control, noticeable adjustments are

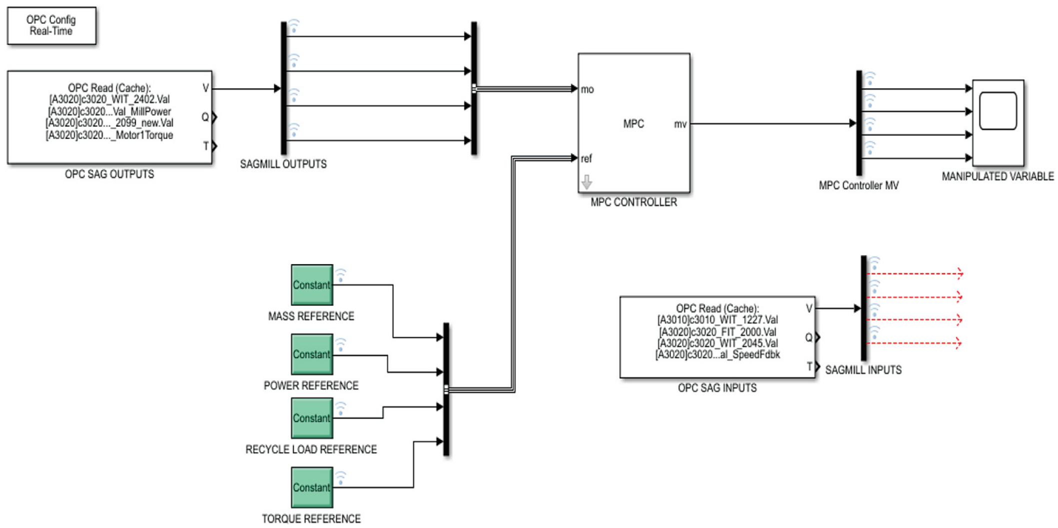


Figure 14. Real time data for the SAG mill with MPC controller

Table 3. Comparison between operator and MPC control, Ref = [570 t, 11200 kW, 100 t/h, -95%]

Time (s)	Sag mill process outputs				Operator control				MPC control			
	Mass	Power	Recycle load	Torque	Feed	WRatio	Pebble	Speed	Feed	WRatio	Pebble	Speed
100	Below ref	Below ref	Above ref	Below ref	No Change	No change	Reduced	No change	Increased	Reduce	Increase	Increase
500	Belowref	Below ref	Above ref	Below ref	No change	No change	Increased	No change	Increase	Reduce	Increase	Increase

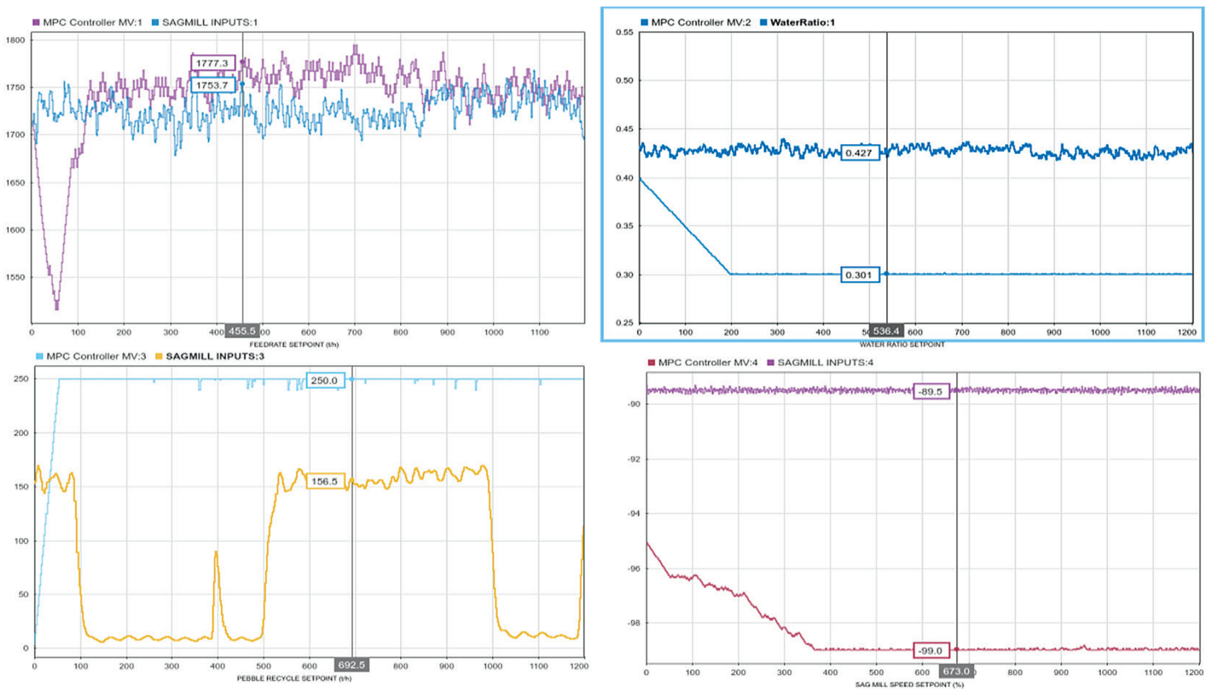


Figure 15. MPC MV vs realtime SAG mill inputs, ref [570 t, 11200 kW, 100 t/h, -95%]

made: an increase in feedrate and pebble recycle feed, an elevation in SAG mill speed, and a reduction in water ratio. These actions are undertaken with the objective of aligning the SAG mill outputs precisely with their predefined setpoints. At the time mark of 500 seconds, where mill mass, power, and torque are still below their respective reference values and recycle load exceeds the reference: operator control inputs predominantly remain unaltered, with the exception of an increase

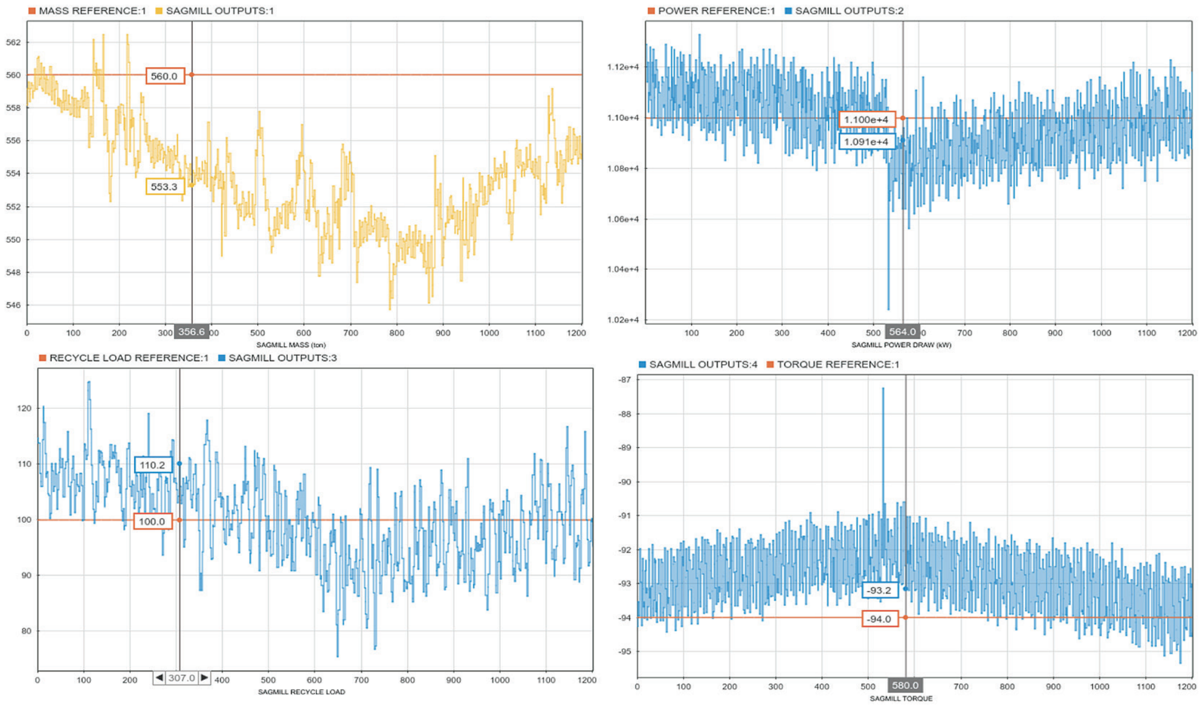


Figure 16. Real-time process outputs vs outputs reference [560t,11000kW,100t/h, -94%]

in pebble feed during this time frame. Conversely, the MPC controller adheres to its strategy initiated at the 100-second mark, with a primary focus on maximizing the mill speed to 99%, elevating the feed rate to 1750 tons/hour, reducing the water ratio to 0.3, and elevating the pebble feed to its maximum rate of 250 tons/hour. It is noteworthy that the control of pebble recycle is overseen by a bin-level system, where the activation or deactivation of the pebble crusher feeder is contingent upon the bin level. The real-time simulation was executed with the process setpoints set at [560 tons, 11000 kW, 100 t/h, -94%]. Table 4 offers an exhaustive comparison of the responses exhibited by both operator and MPC controls in relation to the SAG mill process outputs, as illustrated in Figure 17. These comparisons are conducted under the following circumstances: At the time mark of 200 seconds, where mass and torque are below their designated reference values, and torque and recycle load exceed their predefined levels: In this phase of the real-time simulation, operator control maintains the status quo regarding process input variables, indicating a lack of active response to the changing conditions. Conversely, if the MPC controller were overseeing the process, it would take proactive measures by increasing the feedrate, reducing the water-to-ore ratio, maintaining the pebble feed at a constant level, and decreasing the SAG mill speed to align the mill outputs with their predetermined setpoints. At the time mark of 500 seconds, where mill mass, power, torque, and recycle load are all observed to be below their respective reference values: no significant alterations in operator control inputs are observed since the 200-second mark. Meanwhile, the MPC controller, recognizing that the SAG mill outputs are still not approaching the reference points, continues to adapt by reducing the speed, increasing the feed rate, and raising the water ratio, while keeping the pebble feed constant. At the time mark of 550 seconds, where the recycle load slightly exceeds its reference, while other outputs remain below their defined references: during this phase, the operator is observed to decrease the SAG mill speed by 1% without making changes to other input conditions. In contrast, the MPC controller continues to escalate the feedrate and the water-to-ore ratio. No adjustment is made to the pebble feed (which remains at 0), but a noticeable change in the SAG mill speed is evident as the controller starts to increase it.

The results and analysis of the simulation reveal notable differences in response times between operator control and MPC control of the SAG mill. It's observed that the operator often takes an extended period to react to changes in SAG mill outputs like mill mass, power draw,

Table 4. Comparison between operator and MPC control, Ref = [560t, 11000kW, 100t/h, -94%]

Time (s)	Sag mill process outputs				Operator control				MPC control			
	Mass	Power	Recycle load	Torque	Feed	WRatio	Pebble	Speed	Feed	WRatio	Pebble	Speed
200	Below ref	Above ref	Above ref	Below ref	No change	No change	No change	No change	Increased	Reduced	No change	Reducing
500	Below ref	Below ref	Below ref	Below ref	No change	No change	No change	No change	Increased	Increased	No change	Reducing
550	Below ref	Below ref	Above ref	Below ref	No change	No change	No change	Reduced	Increased	Increased	No change	Increasing

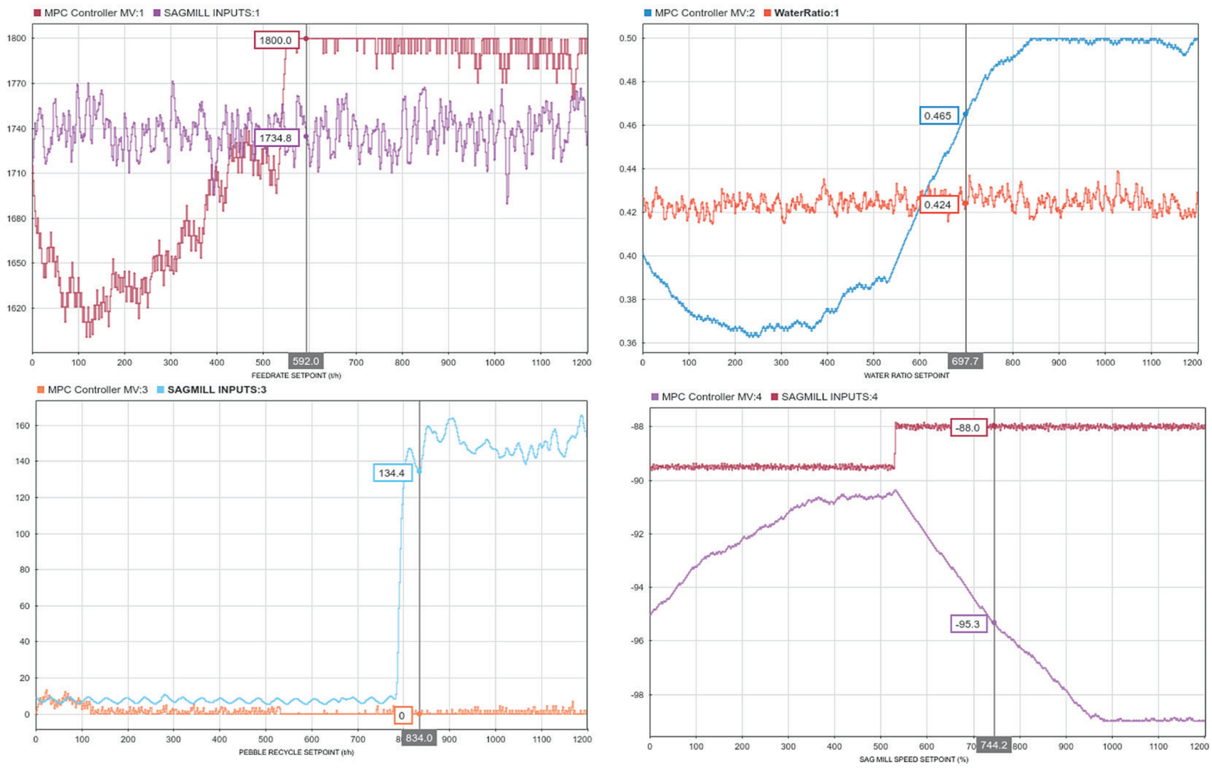


Figure 17. MPC MV vs realtime SAG mill process inputs, reference [560 t,11000 kW,100 t/h, -94%]

recycle load, or torque. In some cases, the operator does not respond until the system reaches a critical condition. Additionally, the operator typically adjusts only one process input variable at a time, waiting to observe the impact of this change on the SAG mill before modifying any other variables. In contrast, the MPC controller exhibits a more proactive approach. It responds promptly to changes in SAG mill process outputs, striving to maintain the controlled outputs at their required or defined reference setpoints. The MPC controller also actively adjusts all control variables as needed to stabilize the SAG mill-controlled outputs. This operational effectiveness of the MPC controller aligns with the operating scenarios outlined by Brian Putland et al. [17]. The actions and control mechanisms of the MPC controller, as demonstrated in Figure 17, show its capability to manage the SAG mill operations more efficiently and responsively compared to traditional operator control.

CONCLUSIONS

This study has achieved the successful development of a MPC utilizing a neural network model derived from historical process data of a SAG mill, leveraging MATLAB's neural network toolbox. The model's precision was validated against both the training data and additional process data. Subsequently, the implemented MPC controller underwent real-time testing, pitted against operator control, which relies on PID setpoints.

The MPC controller has demonstrated its prowess in simultaneously and judiciously adjusting all control variables, a notable departure from operator control, which tends to prioritize one control variable at a time. For instance, operators often resort to diminishing the ore feed-rate to reduce mill mass or lowering the SAG mill speed to increase mill mass. Such strategies, however, tend to have adverse effects on the SAG mill's throughput rate due to reduced feed-rate or compromised mill speed. In contrast, the MPC controller has efficiently overseen the SAG mill by operating it at elevated speeds while concurrently fine-tuning the water-to-ore ratio and augmenting the pebble recycle crushing rate, all the while maintaining a robust ore feed-rate. This underscores the MPC controller's capacity to uphold high throughput rates through strategic manipulation of variables like water-to-ore ratio, SAG mill speed, and pebble crushing recycle rate, instead of relying solely on feed-rate adjustments. Moreover, the MPC controller has exhibited adept control over water usage in the SAG mill, contributing to water conservation and cost reduction. It has also effectively governed the SAG mill's speed, resulting in energy savings and diminished energy consumption costs. These findings underscore the MPC's comprehensive effectiveness in optimizing operational efficiency while concurrently minimizing resource consumption.

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