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A Model Predictive Control for Coal Beneficiation Dense Medium Cyclones

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Abstract: The purpose of the controller presented is to maintain the proportion of carbon content in the products of the coal washing dense medium cyclone (DMC) at a certain level by optimally manipulating the density of the heavy medium. In practice, the DMC processes are mainly controlled by empirical methods which are process specific and cannot satisfy the industrial requirements today. As a result, industries are looking at introducing sensors to monitor the coal quality from the DMC process. Application of such sensors requires the development of new controllers that can handle large delays and sampled measurement. Therefore, a model based closed-loop control approach is presented to improve the separation efficiency of DMC plants. The feed coal quality is taken as the feed forward information and the sampled and delayed measurement from the DMC output is utilized as feedback for the controller to improve the quality of coal product and ensure the robustness of the controller. In addition, a state updating scheme is presented for the controller because the time delay of the measured feedback can be one hour or longer. The effectiveness of the designed controller is demonstrated by simulations.

Keywords: Coal beneficiation, dense medium cyclone, model predictive control, model plant mismatch, delayed and sampled measurement.

1. INTRODUCTION

Improving the process efficiency of coal benefication plants to obtain high quality fine coal for industrial use is of great importance due to energy shortage and the pressure on carbon footprint mitigation. The run-of-mine (ROM) coal contains many different contents like rock, ash, sulfur, volatile, etc., which are to be removed by the coal washing process. If the coal is not cleaned thoroughly, the non-carbon contents will have a deterministic effect on the quality (e.g. heating value) of the coal (Speight, 2005). For instance, the carbon content cannot be fully burnt, which results in waste of coal resources. In practice, removing all the non-carbon components cannot be easily realized. Therefore, the percentage of fixed carbon content in the fines is usually used as a measure for assessing the quality of the fine coal (Nurkowski, 1984; Kolker et al., 2006).

From the view point of coal processing companies, they are forced to improve the quality of their products and reduce energy consumption due to market competition and the sharp rising energy price. Dense medium cyclones (DMCs) are used as the main coal benefication process in modern coal washing plants because of their high capacity and efficiency (Chu et al., 2009). The relative density of the dense medium used to enhance the separation is the key factor that affects the quality of coal after this DMC circuit. As the characteristics of the ROM coal vary, a proper control is essential to ensure the fine coal quality. Historically, this is done by manually adjusting the medium density (Burgess, 1984) or applying control theory to an experimental DMC model obtained by data fitting (Firth, 2009; Addison, 2010). Drawbacks of the empirical approaches are twofold. Firstly, detailed information of different components (fixed carbon, ash, sulfur, etc.) in the fine product is missing. Secondly, the structure and parameters of the cyclone model are process specific and have no clear physical meanings. Under the extreme case, the empirical model is only applicable to the cyclone on which the experiments were carried out.

In view of this, a model-based optimal control approach is highly desired. An optimal feed forward controller for the DMC coal beneficiation process was proposed in our previous study (Zhang et al., 2013) based on a general DMC model which was developed and validated by Meyer and Craig (2010). But, no feedback information on coal quality was taken into account in that study because measurement of required information at the DMC output takes around four hours and is very costly. Recently, driven by the market force and coal quality requirements, coal mining companies are looking for opportunities in improving the separation efficiency of the DMC processes by investing in equipment that measures the quality of DMC products. The new equipment is capable of measuring the coal quality with less than one hour's delay. However, the new sensor only gives sampled measurement. Both the sampled measurement and the long time delay pose technical problems for the design of a feedback solution. On the one hand, it requires the controller to be able to deal with sampled and delayed measurement feedback. On the other hand, controls by sampled and delayed output measurement are of very acute control theoretical interests (Ahmed-Ali et al., 2013; Lee et al., 2013), little effort is made to test these new ideas in the DMC study.

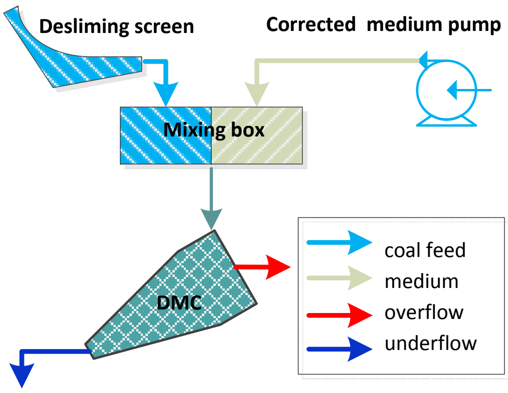

Fig. 1. Diagram of DMC coal separation circuit

In this study, a closed-loop model predictive control (MPC) approach is employed to optimize the behavior of the DMC plant. As one of the most effective control approaches in industrial field (Xia et al., 2011; Zhuan and Xia, 2013; Elaiw et al., 2012; Qin and Badgwell, 2003) and with the ability of dealing with constraints (Zhang and Xia, 2011), MPC has some intrinsic properties that make it suitable for this application. For instance, the state prediction under measurement delay is highly desirable for the DMC control. With the delayed and sampled measurement, the state of the DMC predicted by an emulation approach is used by the MPC when no actual measurement is available.

The closed-loop control is introduced to determine the optimal control based on the results of the feed forward controller (Zhang et al., 2013) such that the performance of the DMC can be improved, especially under the presence of model plant mismatch and disturbances. In such a way, both feed forward and feedback information on coal quality are taken into account to reach desired DMC behavior. Results of the feed forward optimal controller in our previous paper are used as the baseline to demonstrate the advantages of this design.

Benefits of this design can be summarized as follows:

- Feed coal characteristics are taken into account, which make the proposed controller robust against the variation of the ROM coal quality.
- A closed-loop controller is designed so that performance of the DMC circuit is maintained under disturbances and model plant mismatch.
- The controller is applicable to similar DMC circuits because it is designed based on a general DMC model.
- It provides a test platform for delayed and sampled control system.

The remainder of this paper is organized as follows. The model of the DMC circuit is briefly described in Section 2, this is followed by the controller design in Section 3. Simulations are given in Section 4 to demonstrate and verify the effectiveness of the proposed control approach. Section 5 concludes this paper.

2. DMC COAL SEPARATION PROCESS

The ROM coal and corrected dense medium are fed to a mixing box where they are blended before entering the DMC as shown in Fig. 1. According to the percentages of the components in the ROM coal $x_{ore,c}$, in which the subscript c represents ash, sulfur, moisture, and volatile, the percentages of those components $x_{i,c}$ and medium $x_{i,m}$ in the mixed slurry fed into the DMC can be calculated by the following equations (Meyer and Craig, 2010).

$$\dot{\rho}_{mb} = -\frac{Q_{mb}}{V_{mb}}\rho_{mb} + \frac{Q_{mb,m}}{V_{mb}}\rho_{mb,m} + \frac{1}{V_{mb}}W_{ore}, \quad (1)$$

$$x_{i,c} = \frac{x_{ore,c}W_{ore}}{Q_{mb}\rho_{mb}}, \quad (2)$$

$$x_{i,m} = \frac{Q_{mb,m}\rho_{mb,m}}{Q_{mb}\rho_{mb}}, \quad (3)$$

where ρ_{mb} is the density of the mixed slurry from the output of mixing box. V_{mb}, $Q_{mb,m}$, $\rho_{mb,m}$ and W_{ore} are, respectively, the volume of the mixing box, the medium flow rate, the medium density, and the coal feed rate to the mixing box. Q_{mb} is the flow rate of the mix to the cyclone.

The relationships between the proportions of different components in the slurries that enter and exit the DMC are governed by the following equations (Meyer and Craig, 2010).

$$\begin{aligned}
\dot{x}_{o,c} =& \frac{1}{V_o\rho_o}\big[W_i x_{i,c} - Q_o\rho_o x_{o,c} - Q_u\rho_u x_{u,c} - V_o x_{o,c}\dot{\rho}_o \\
&- V_u x_{u,c}\dot{\rho}_u - K_{u,c}V_u\rho_u(\rho_c - \rho_{mb,m})(x_{i,c} - x_{u,c})\big], \\
\dot{x}_{u,c} =& \frac{1}{V_u\rho_u}\big[W_i x_{i,c} - Q_o\rho_o x_{o,c} - Q_u\rho_u x_{u,c} - V_o x_{o,c}\dot{\rho}_o \\
&- V_u x_{u,c}\dot{\rho}_u - K_{o,c}V_o\rho_o(\rho_{mb,m} - \rho_c)(x_{i,c} - x_{o,c})\big], \\
\dot{x}_{o,m} =& \frac{1}{V_o\rho_o}\big[W_i x_{i,m} - Q_o\rho_o x_{o,m} - Q_u\rho_u x_{u,m} \\
&- V_o x_{o,m}\dot{\rho}_o - V_u x_{u,m}\dot{\rho}_u \\
&- K_{u,m}V_u\rho_u(\rho_{o,m} - \rho_{mb,m})(x_{i,m} - x_{u,m})\big], \\
\dot{x}_{u,m} =& \frac{1}{V_u\rho_u}\big[W_i x_{i,m} - Q_o\rho_o x_{o,m} - Q_u\rho_u x_{u,m} \\
&- V_o x_{o,m}\dot{\rho}_o - V_u x_{u,m}\dot{\rho}_u \\
&- K_{o,m}V_o\rho_o(\rho_{mb,m} - \rho_{u,m})(x_{i,m} - x_{o,m})\big], \\
\dot{\rho}_o =& \frac{1}{V_o}\big[W_i - Q_o\rho_o - Q_u\rho_u - K_u V_u(\rho_u - \rho_{mb,m})x_{i,ash}\big], \\
\dot{\rho}_u =& \frac{1}{V_u}\big[W_i - Q_o\rho_o - Q_u\rho_u - K_o V_o(\rho_o - \rho_{mb,m})x_{i,C}\big],
\end{aligned} \quad (4)$$

where $x_{o,c}$, $x_{u,c}$ are 4×1 vectors that represent the percentages of components (ash, sulfur, moisture and volatile) in the overflow and underflow of the cyclone, respectively. ρ_o and ρ_u are the densities of slurries exiting at the overflow and underflow of the cyclone. $W_i = Q_{mb}\rho_{mb}$ is the slurry feed rate to the cyclone. The volumetric parameter V_c denotes the volume of slurry inside the cyclone which is assumed to split at a constant ratio α into the volume that reports to the overflow $V_o = \frac{\alpha}{1+\alpha}V_c$ and the volume that reports to the underflow $V_u = \frac{1}{1+\alpha}V_c$. Similarly, Q_o and Q_u are the flow rates to the overflow and underflow of the cyclone that are split by the same ratio α. The $K_{o,c}$, $K_{u,c}$, $K_{o,m}$ and $K_{u,m}$ are DMC specific constants for the component overflows and underflows.

The percentages of fixed carbon in the cyclone overflow and underflow after medium recycling, $x_{o,C}$ and $x_{u,C}$, are obtained by the following equations.

$$x_{o,C} = 1 - \frac{1}{1 - x_{o,m}} \sum_c x_{o,c},$$
$$x_{u,C} = 1 - \frac{1}{1 - x_{u,m}} \sum_c x_{u,c}. \quad (5)$$

The model represented by equations (1)—(5) is derived from the model developed by Meyer and Craig (2010). The advantage of this model is that the percentages of different components in the cyclone products and rejects can be obtained directly so that a controller can be designed to optimize the DMC process in a more detailed manner in comparison to the empirical approaches (Napier-Munn, 1991).

3. CONTROL OF DMC PROCESS

In order to maintain the coal quality at a specified level, there is need of a well designed controller. Due to the fact that the DMC process model is intrinsically nonlinear, a nonlinear model predictive controller is proposed to control the relative density of the medium.

To facilitate controller design, the DMC model is discretized using the Runge–Kutta method to be as follows

$$x(k+1) = f(x(k), u(k)), \quad (6)$$

where the state of the DMC process at time kT_s is $x(k) = [x_{o,c}^T(k), x_{u,c}^T(k), x_{o,m}(k), x_{u,m}(k), \rho_o(k), \rho_u(k)]^T$, in which T_s is the sampling period. $f(\cdot)$ is the nonlinear functions that represent the DMC model. The control variable is $u(k) = \rho_{mb,m}(k)$.

3.1 Feed forward control

The primary goal of controlling the DMC process is to maintain the quality of the coal. With the sharp increase of electricity price in recent years, improving energy efficiency of the DMC plant is also of vital importance for the economic benefit of the plant owner. Therefore, reducing energy consumption is treated as the secondary objective of the controller. As a result, the following objective function is adopted.

$$J = \sum_{k=1}^{T/T_s} \left[k_p (x_{o,C}(k) - x_r(k))^2 + k_e u(k)^2 \right], \quad (7)$$

where $x_r(k)$ is the desired percentage of fixed carbon in the fines, T is the operating time of the DMC circuit. For simplicity, T is a multiple of T_s. Weights k_q and k_e are used to tune the controller, which are chosen by users according to the preference for coal quality and energy consumption.

The first and second terms in this function represent, respectively, the indicators of coal quality and energy consumption. The reasonability of using u^2 as a indicator for energy consumption lies in the fact that the dense medium is pumped to the mixing box. The energy consumed by the DMC circuit is mainly the pumping cost which is a linear function of the medium density.

The physical constraints of the DMC process include the maximum and minimum limits of the density of the medium, and limits on the percentages of the components in the mixture. The operational constraints are the limits on the rate of change of the medium density. In summary, the constraints are given in the following inequalities.

$$0 \le x_{o,c}(k) \le 1, \quad (8)$$
$$0 \le x_{u,c}(k) \le 1, \quad (9)$$
$$0 \le x_{o,C}(k) \le 1, \quad (10)$$
$$0 \le x_{u,C}(k) \le 1, \quad (11)$$
$$|\rho_{mb,m}(k) - \rho_{mb,m}(k-1)| \le \Delta\rho_m, \quad (12)$$
$$\rho_{mb,m}^l \le \rho_{mb,m}(k) \le \rho_{mb,m}^u. \quad (13)$$

Inequalities (8), (9), (10), and (11) naturally exist as the percentages are from 0% to 100%. Constraints (12) and (13) represent the limits on the rate of change and range of the medium density. $\Delta\rho_m$, $\rho_{mb,m}^l$ and $\rho_{mb,m}^u$ are, respectively, the limits on the rate of change, and the lower and upper limits of the density of the medium.

In practice, the percentages of components in as well as the feed rate of the ROM coal feed are measured. Therefore, the feed forward controller solves the nonlinear optimization problem, minimize (7) subject to (6) and (8)–(13), with help of these measurements.

3.2 Closed-loop MPC for DMC circuits

Whereas the feed forward controller takes advantage of feed forward information to optimize the DMC performance, it is essentially an open loop controller. In order to control the DMC plant effectively under model plant mismatch and process disturbances, a closed-loop MPC controller is proposed in this study.

In MPC, the optimal solution of the original problem is obtained step-by-step by solving the problem within each chosen optimization window where feedback information from the plant can be incorporated into the optimization. This feedback information results in improved robustness of the controller with regard to model plant mismatch and process disturbances.

Specifically, the MPC controller designed aims to improving fine coal quality by means of manipulating the density of medium in real-time according to the feedback state of the DMC outputs.

Denote the DMC state and control reached by the feed forward controller as x^0 and u^0, in which the carbon content is denoted as $x_{o,C}^0$. The closed-loop MPC is to maintain the carbon content taking advantage of feedback information x by introducing Δu change to u^0, $u = u^0 + \Delta u$. Therefore, the objective function for the closed-loop MPC is derived from (7) and given as follows

$$\begin{aligned} J = \sum_{i=1}^{N_p} \Big(& k_p \Delta x_{o,C}^2(k+i|k) + k_e \Delta u(k+i-1|k)^2 \\ & + 2k_p [x_{o,C}^0(k+i) - x_r(k+i)] \Delta x_{o,C}(k+i|k) \\ & + 2k_e u^0(k+i-1) \Delta u(k+i-1|k) \Big), \end{aligned} \quad (14)$$

where N_p is the optimization horizon, k denotes the current time kT_s, $|k$ means that the predicted value is based on the information available from $t = 0$ up to

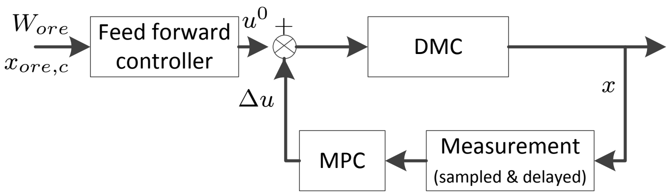

Fig. 2. Control diagram

$t = kT_s$, and $\Delta x_{o,C} = x_{o,C} - x^0_{o,C}$ is the change of carbon content resulted from Δu.

As for the constraints, they are transformed into

$$h(\Delta u(k|k), \ldots, \Delta u(k + N_c - 1|k)) \leq \gamma, \qquad (15)$$

where N_c is the control horizon. The nonlinear function $h(\cdot)$ represents the constraints (8)—(13) and γ represents the limits derived therein.

As depicted in Fig. 2, the feed forward controller is an open loop controller that optimizes the performance of the DMC taking into account the feed coal characteristics (W_{ore} and $x_{ore,c}$). Feedback information from output of the cyclone is used by the closed-loop MPC controller to improve the behavior of the DMC under model plant mismatch and external disturbances. The optimal medium density is obtained by adding up the solutions of the feed forward and the feedback controllers: $u = u^0 + \Delta u$.

Therefore, the MPC forms a state feedback control that solves the problem, minimize (14) subject to (15), iteratively.

To close the loop, measured feedback from the output of the DMC is required. This measurement for the DMC plant is obtained by the new sensor, which yields sampled values at discrete time instances with less than one hour time delay (indicated in Fig. 2). This sampled and delayed measurement causes a time interval within which there is no feedback information from the DMC circuit. As a result, the state of the DMC system is predicted by the DMC model and updated whenever actual measurement is available. Fig. 3 shows the scheme of the state prediction.

Assume that the measurements are only available at time $t_1, \ldots, t_i, \ldots, t_n$, the state of the DMC is predicted as

$$x(t) = \hat{x}(t|t_i), \ t_i < t < t_{i+1},$$

where the symbol $\hat{x}(t|t_i)$ represents the state of the DMC process at time t predicted by the DMC model according to measurement information at time t_i.

During the time interval within which no measurement is received, the state predicted based on the most recent measurement information is used by the controller. The measurement data are the feedback for the controller to: 1) calibrate the modeling error and 2) improve the behavior of the DMC process according to the actual state. Under process disturbances and model plant mismatch, this feedback information is essential to ensure the robustness of the control system.

The work flow of the proposed nonlinear MPC controller is depicted in **Algorithm 1**, where the procedure of state feedback, optimization and control are demonstrated.

Algorithm 1 Nonlinear MPC for DMC circuits

Initialization: model parameters, optimization and control horizons.
while $t < T$ **do**
  if measurement available **then**
    Update prediction to be $\hat{x}(t + i|t)$.
  end if
  Solve the optimization problem within the optimization horizon to obtain the feedback control vector $\Delta u = [\Delta u(1), \ldots, \Delta u(N_c)]$.
  Apply the control variable $u^0(t) + \Delta u(1)$ to the DMC plant.
end while

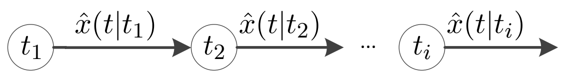

Fig. 3. State prediction under sampled and delayed measurement

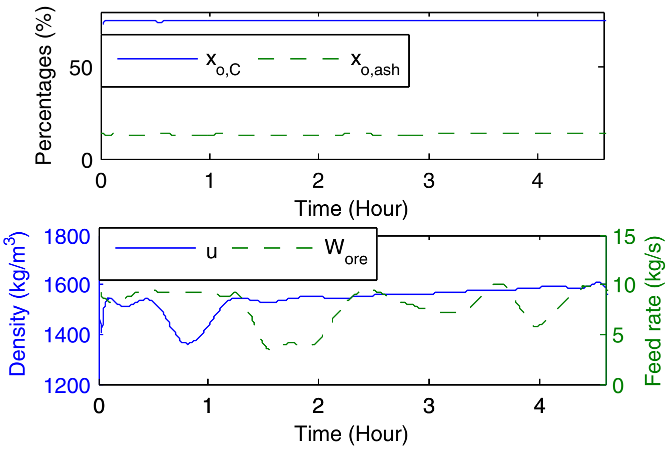

Fig. 4. Closed-loop MPC results under ideal case

4. SIMULATION

Simulations are done based on the plant data from a coal washing plant in South Africa. The DMC parameters are retrieved from (Meyer and Craig, 2010) and listed in Table 1. Sampling period T_s is taken as 14 seconds. The optimization and control horizon N_p and N_c are set to 5 and 3, respectively. The set carbon proportion in the fine coal is kept constant as 75%. The weights for product quality and energy consumption are chosen as $k_p = 5000$ and $k_e = 1 \times 10^{-6}$. The optimization is done over a simulation period of T equals to 5 hours.

It is noted that the feed forward controller is essentially an open loop controller and its results are taken as reference to investigate the advantages of the designed control approach. In simulations, the results of the feed forward controller are referred to as open loop results, which take 5 minutes of a PC with Intel i7-2600 core to solve with Matlab 2010b.

To demonstrate the effectiveness of the proposed control strategy, the MPC results without model plant mismatch and disturbances are shown in Fig. 4. As this is the ideal case, it shows that the density of the medium is varied

Table 1. Cyclone separation circuit model parameters

Variable	Description
V_{mb}	0.16 (m^3)
$Q_{mb,med}$	0.495 (m^3/s)
Q_{mb}	0.500 (m^3/s)
α	2
V_c	0.38 (m^3)
K_o	0.22 (m^2s)
K_u	0.22 (m^2s)
$K_{o,ash}$	2.00×10^{-4} (m^3/kgs)
$K_{o,S}$	3.90×10^{-4} (m^3/kgs)
K_{o,H_2O}	1.50×10^{-4} (m^3/kgs)
$K_{o,vol}$	8.90×10^{-4} (m^3/kgs)
$K_{o,med}$	4.80×10^{-4} (m^3/kgs)
$K_{u,ash}$	0.77×10^{-4} (m^3/kgs)
$K_{u,S}$	3.90×10^{-4} (m^3/kgs)
K_{u,H_2O}	0.30×10^{-4} (m^3/kgs)
$K_{u,vol}$	8.90×10^{-6} (m^3/kgs)
$K_{u,med}$	3.90×10^{-4} (m^3/kgs)
ρ_{ash}	2000 (kg/m^3)
ρ_S	1920 (kg/m^3)
ρ_{H_2O}	1000 (kg/m^3)
ρ_{vol}	1100 (kg/m^3)

in such a way that the carbon percentage in the product is kept constant. The key factor that affects the medium density in this case is the ROM coal feed rate.

4.1 Model plant mismatch

In practice, the model used for controller design usually cannot exactly capture the behavior of the plant accurately. Assume that there is d mismatch between the model and the plant, which means that the true plant model is given by

$$x(t) = f(x(t-1), u(t-1)) + d(t).$$

Under the sampled and delayed measurement, the state predicted according to the most recent measurement, $\hat{x}(t|t_i)$, is used in the optimal control during the time interval $[t_i,\ t_{i+1})$. This means that, during the period $[t_i,\ t_{i+1})$, the control is not based on the actual plant state, which results in control errors. In the closed-loop approach, the measurement data are used to eliminate prediction errors from the model and resultantly eliminate the control errors and improve the performance of the DMC.

A 5% modeling error is considered since it has been verified by Meyer and Craig (2010) that the DMC model developed is able to predict the plant behavior within 5% error with 95% confidence. Specifically, the modeling error d is assumed to be:

$$d(t) = 0.05x(t)(-1 + 2\epsilon(t)),$$

where ϵ is a vector with uniformly distributed random numbers on [0,1].

A comprehensive comparison of the DMC performance between the closed-loop MPC approach and the open loop controller is shown in Fig. 5, in which the 5% model plant mismatch is introduced for all circumstances. $|e|$ in the figure stands for absolute mean tracking error of the controller.

According to the results, it is clear that the open loop control strategy for the DMC plant suffers from carbon proportion deviation in the fine product. 2.09% mean deviation from the set value is observed during the 4.9 hour simulation. To improve this, a closed-loop approach is desirable. All closed-loop results are better than the open loop results as demonstrated in the Fig. 5. For instance, the MPC results with one hour measurement delay results in 0.70% deviation in the carbon percentage, which is one third of that with the open loop control.

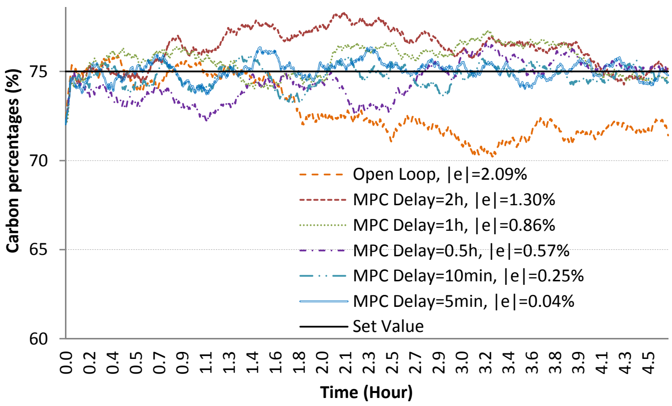

Fig. 5. Performance comparison under model plant mismatch and varying measurement delay

4.2 Measurement delay

Measurement of coal quality from the DMC process usually takes several hours. For the mine under investigation, it is planning to install a the new sensor that could shorten this delay to less than one hour. Consequently, to ensure the applicability and effectiveness of the controller, the controller's tolerance on the measurement delay is investigated. Up to two hour measurement delays are investigated, which is suffice for practical application as the measurement delay in practice is less than one hour.

As illustrated in Fig. 5, one can see that the larger the measurement delay, the worse the performance of the controller. $|e|$ of those results shows a decreasing trend with the decrease in the measurement delay. Specifically, the tracking error with the open loop control is largest (2.09%) while it is smallest with five-minute measurement delay (0.04%).

Considering that the measurement delay is less than one hour in practice, the closed-loop MPC approach achieves the goal of keeping carbon content constant with less than or equal to 0.7% tracking error. In comparison with the open loop strategy, the MPC reduces the tracking error by more than 66.5%. This verifies that, even though the DMC feedback information is measured in a sampled and delayed manner, the proposed MPC strategy can improve the performance of the DMC plant significantly.

4.3 Implementation disturbance

Disturbance from implementing the optimal control is considered here. For the DMC plant, the valve control for the water and make-up medium addition module in the DMC plant results in disturbances in the optimized density of the medium. Therefore, robustness against the

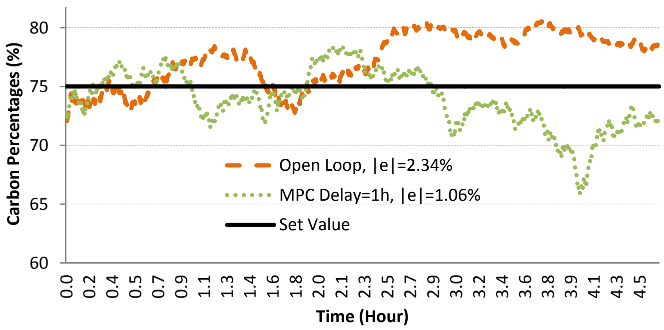

Fig. 6. Closed-loop MPC v.s. open loop control under disturbances

actuator disturbances is essential for the control approach proposed. Simulations are also conducted to verify this.

In simulations, an implementation disturbance is introduced to the control signal, which leads to

$$u_d = u + w,$$

where w is the white Gaussian noise.

The disturbed control signal u_d instead of the optimized u is implemented to the DMC plant in such a situation. The performance of the closed-loop MPC controller and the open loop controller are again compared to investigate the robustness of the closed-loop MPC controller.

It is observed from Fig. 6 that, not surprisingly, the closed-loop MPC approach is more effective in achieving desired DMC performance in comparison to the open loop control. Note that the 5% model plant mismatch is also considered in this simulation.

The mean values of the deviations from the specified 75% carbon content in the fines are 2.34% and 1.06% with the open loop controller and the closed-loop MPC with one hour measurement delay, respectively. This verifies that the closed-loop MPC approach is capable of keeping the carbon content in the fines to the desired level under the disturbance from implementing the optimized control.

5. CONCLUSION

This study investigates the feasibility and advantages of designing a closed-loop control approach to improve the separation efficiency of coal beneficiation dense medium cyclones in the presence of large delay and sampled measurement feedback. A model predictive control approach, which takes advantage of both the feed forward information on the run-of-mine quality and the delayed fine coal quality measurement, is proposed to improve the efficiency of the dense medium cyclone plant. The density of the heavy medium used to enhance the separation is taken as the control variable. It is illustrated by simulations that the controller can achieve desired performance with up to two hour measurement delay. In addition, the controller is designed based on a general cyclone model, which ensures its applicability to similar dense medium cyclone circuits.

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