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Predictive Controller Design for a Cement Ball Mill Grinding Process under Larger Heterogeneities in Clinker Using State-Space Models

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Abstract: Chemical process industries are running under severe constraints, and it is essential to maintain the end-product quality under disturbances. Maintaining the product quality in the cement grinding process in the presence of clinker heterogeneity is a challenging task. The model predictive controller (MPC) poses a viable solution to handle the variability. This paper addresses the design of predictive controller for the cement grinding process using the state-space model and the implementation of this industrially prevalent predictive controller in a real-time cement plant simulator. The real-time simulator provides a realistic environment for testing the controllers. Both the designed state-space predictive controller (SSMPC) in this work and the generalised predictive controller (GPC) are tested in an industrially recognized real-time simulator ECS/CEMulator available at FLSmidthPvt. Ltd., Chennai, by introducing a grindability factor from 33 to 27 (the lower the grindability factor, the harder the clinker) to the clinkers. Both the predictive controllers can maintain product quality for the hardest clinkers, whereas the existing controller maintains the product quality only up to the grindability factor of 30.

Keywords: ball mill grinding; state-space model; predictive controller; real-time simulator

1. Introduction

The annual cement consumption in the world is around 1.7 billion tonnes and is increasing by 1% every year [1]. Cement industries consume 5% of the total industrial energy utilised in the world [2]. A total of 40% of the total energy consumption of a cement plant is used in clinker grinding in a ball mill to produce the final cement product [3]. Figure 1 shows the percentage of energy usage in various stages of the cement manufacturing unit [4]. Under this scenario of extensive energy usage in clinker grinding, the cement industries not only require the proper mechanical design aspect of the grinding unit but also necessitate suitable and efficient controllers that result in a reduced energy consumption per unit production of cement. Another significant fact in the cement manufacturing process, especially in the indigenous ball mill grinding unit, is that the variations in the hardness of the clinkers (grindability factor) affect the product quality and productivity. In the competitive cement market, it is very much essential to improve the product quality and productivity under reduced energy consumption. Under this scenario, it is a challenging task for the control engineers to design suitable controllers for the cement ball mill grinding process, even in the presence of larger grindability variations.

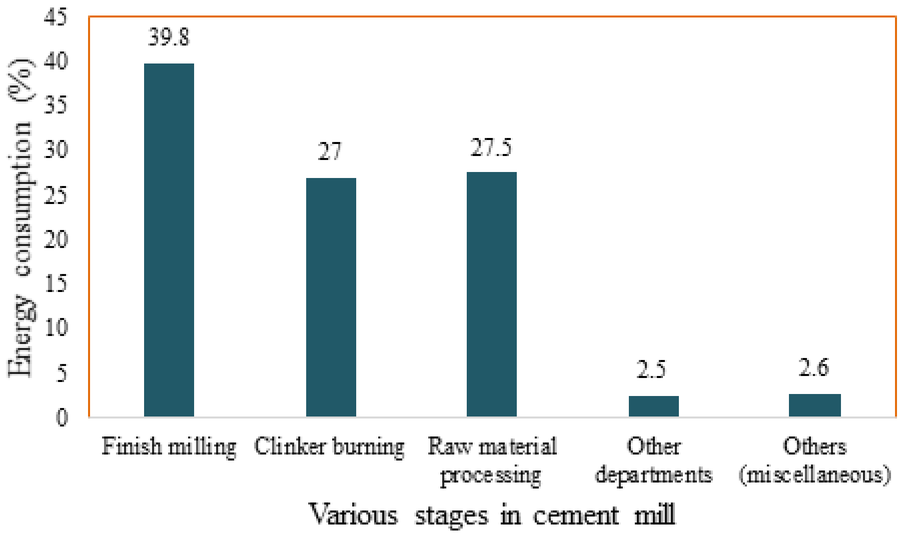


Figure 1. Percentage of energy consumption in the cement manufacturing sector.

Motivated by this, an attempt is made to design a predictive controller using a state-space model of the cement grinding circuit to provide optimum productivity with a better quality under reduced energy consumption by operating the plant closer to actuator constraints even in the presence of variations in the grindability factor of the clinker as a disturbance. The existing controllers [5–25] for the cement grinding circuit that is available in the literature suffer from some or all of the following drawbacks.

- Unable to operate the plant closer to constraints;
- Challenging the product quality under larger variations in the grindability factor;
- Use of the first principle model to design controllers that do not capture the plant dynamics effectively;
- Saturation of the selected manipulating variables beyond certain limits;
- Difficulty in the measurement of some of the process variables.

The classical Proportional Integral Derivative (PID) controllers for the grinding mill is addressed in [5]. Though the control technique is cheap and more comfortable for implementations, they suffer from model uncertainties. The deterioration of the performance due to disturbance and noise in the classical controllers were handled expertly by fractional-order controllers [6]. The effect of model uncertainties in performance degradation in the PID controller is well managed by introducing loop shaping techniques [7]. Van Breusegem et al. [8–10] designed and implemented linear quadratic (LQ) regulator-based controllers for the cement grinding process that resulted in better performance, however operating the plant closer to constraints was not possible in those controllers, which was the deciding factor for the energy consumption.

Boulvin et al. [11] developed LQ controllers based on material flow rates in and out of the process rather than the material hold up in the ball mill, which depicts the process dynamics. Simple and reliable cascade controller-based Proportional Integral (PI) controllers and feedforward controllers were proposed in [12]. However, the measurement of material flow rates was not easier. Costea et al. [13] developeda fuzzy logic-based control architecture in which the ball mill grinding process was considered as a single input and single output system (SISO) and the total feed into the mill was maintained by manipulating fresh feed flow. However, in reality the process considered here is a multi-input and multi-output (MIMO) system that involves multi-loop interactions.

Intelligent controllers based on fuzzy logic infusion with decentralised PID controllers were designed and tested in the real-time plant [14]. Several intelligent controllers designed based on fuzzy logic [13–16] for the cement ball mill grinding process were able to track the setpoint and reject the disturbance better than the classical controllers addressed in [5–12]. However, the techniques discussed in [13–15] did not address the constraints and roughly handled the manipulation. A genetic algorithm-based fuzzy logic controller designed for the grinding process addresses the stabilisation of the plant [15]. However, maintaining the product quality is also a prime factor to be considered while developing control algorithms which is not addressed in [16] also. Controllers were developed for the cement grinding process based on a linear neuro-fuzzy model by fusing Kalman filter information [17]. The product and reject flow rates were controlled. However, for optimising the cement plant, apart from productivity the product quality is a significant variable to be maintained.

Neural network-based controllers were suggested for the cement mill [18]. The process model considered in this study is based on first principles which did not exhibit the process dynamics of the real-time scenario. A hybrid model was developed for controlling the cement ball mill grinding process that ensured the stable operation of the plant by avoiding the plugging phenomenon [19]. The smooth and stable running of the process can be achieved by maintaining mill load and elevator load with the optimum constant set point. However, the profit margins can be achieved by the cement manufacturer only when the productivity and product quality are improved under reduced energy consumptions. Several predictive controllers are successfully implemented for different processes, such as electric vehicle and fermentation processes, by the research community [20,21]. Though predictive controllers were developed for the cement grinding process in [22–24] to operate the plant closer to constraints, the models considered for prediction were based on the first principles, which capture the noise dynamics badly. In the literature, the separator speed is considered as the manipulating variable. When choosing the separator speed as the manipulating variable, it reaches saturation, and separation becomes inefficient for larger variations in the grindability factor.

The first principle-based model predictive controller developed in [24] lacks measuring the material inside the mill, which is one of the significant process variables to be maintained. The stabilisation of the cement grinding mill was studied by Grognard et al., [25] using a state feed-back controller. The model predictive controller was designed in [26] to operate the grinding mill closer to constraints which ensured a reduced energy consumption per unit of production. However, the product quality deteriorates in the presence of larger variations in the grindability factor of clinker. Since one of the manipulating variables, the separator speed, attains saturation beyond certain limits. The neural network-based controllers were suggested by Topalov et al., [27,28]. However, the controllers developed based on these non-parametric models lead to computational complexity in the real-time environment. A generalised predictive controller was suggested for the cement grinding process [29] based on the transfer function models.

From the above discussions on the literature, it is clear that the models used for controlling the cement grinding circuit are based on the first principle model, which may not capture the real-time plant dynamics in the presence of external noise and disturbance. Moreover, the constraints on the manipulating actuators that decides the energy consumption of the process were not addressed in all the controllers, excepting for the predictive one. All the control schemes used the separator speed as one of the manipulating variables that may not guarantee the desired fineness of the cement product in the presence of larger variations in the feed grindability, since it may attain its maximum value.

Motivated by this research gap, an attempt is made to design a predictive controller based on the state-space model of the cement grinding process. The resultant controller may guarantee the product quality and better productivity even in the presence of larger variations in the feed grindability. This controller may also reduce the energy consumption. The state-space model is obtained from real-time data from the plant. The reason for choosing the state-space technique to build the model of the process is it has the following advantages.

- Quicker estimation because of its requirement of only one input that is model order alone.
- The internal states other than output can be measured or estimated.
- Ease of modeling multivariable systems.
- Non-linear and time-varying systems can be modeled effectively.

- Ease of estimation of internal states of the process. Apart from the above advantages, model predictive controllers based on state-space models were successfully implemented in several industrial applications [30–33].

The main contributions of the investigations are:

- To design the predictive controller for the cement ball mill grinding process based on the state-space model of the process;
- To test the GPC discussed in [29] and the state-space model predictive controller in the simulation;
- To analyse the performance of GPC and the SSMPC in the industrially recognised real-time simulator available in FLSmidthPvt. Ltd., Chennai;
- To compare the performance of GPC and SSMPC with the existing controller addressed in [26].

2. Cement Ball Mill Process

The process taken in this study is an indigenous grinding unit located near Chennai. The schematic diagram of cement ball mill grinding circuit is shown in Figure 2. The clinker, along with additives viz. gypsum, slag, and/fly ash, called feed minerals, are introduced into the horizontally placed ball mill, which consists of steel balls of different sizes. The impact of these balls with feed materials causes grinding and they are lifted by a vertical elevator to the separator. The separator works on the principle of centrifugal force to segregate fine and coarse particles. The finished cement particles satisfying the desired fineness are collected by separator fan and are suspended in the separator air stream to the baghouse. On the contrary, the coarse and semi-ground particles are collected as the rejects at the bottom of the separator and re-circulated into the ball mill for further grinding.

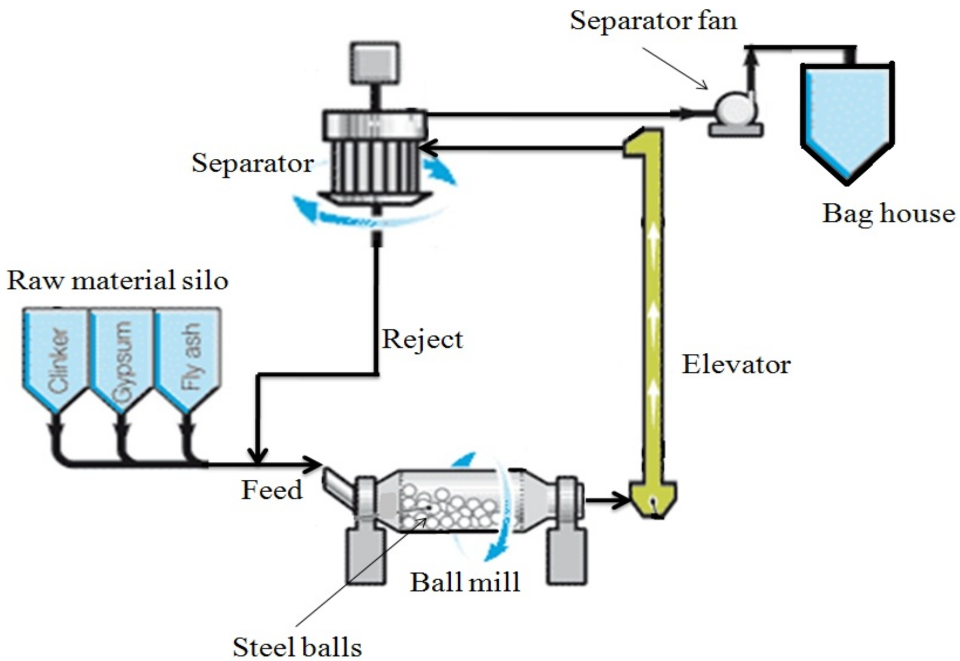


Figure 2. Block schematic of the cement ball mill grinding process.

Suitable controllers are essential to maintain the optimum material inside the mill to get the desired product quality and productivity under a reduced energy consumption. Excessive material inside the mill causes the obstruction of mill, called plugging, which stops the mill from further grinding. On the other hand, a smaller amount of material inside the mill causes wear and tear of the balls and increases the energy per unit production of cement.

Modeling of Cement Ball Mill Process

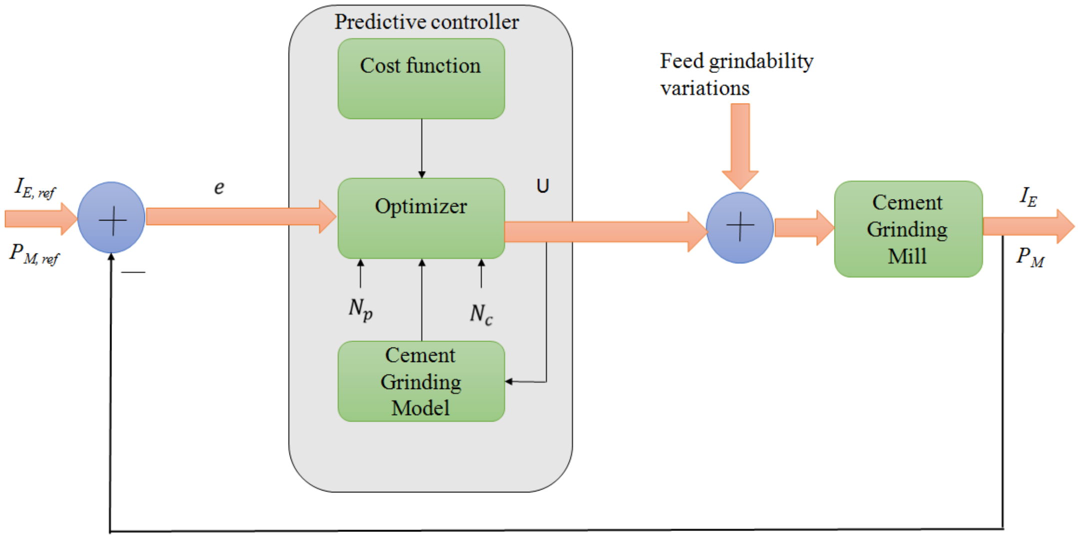
The process considered in this study is an indigenous ball mill grinding circuit located near Chennai. They procure clinkers from different places across the country. Hence, the characteristics of the clinkers from different mills vary to a large extent. An important characteristic that is considered in this work is the grindablity factor. This is the measure of clinker hardness. The nominal grindability factor for the clinker is 33, which is a dimensionless quantity [29]. The grindability factor of the clinker is analysed in the laboratory. Harder clinkers have a lower grindability factor and vice versa. Since the clinkers are procured from different mill across the country, the grindability varies to a larger extent. For modelling the ball mill grinding process, the suitable control strategy is to be established for this indigenous grinding unit to ensure product quality and productivity under optimised energy consumption, even in the presence of larger variations in the grindability factor of the clinker fed into the mill. Under this scenario, it is a challenging task for the control engineers to choose the proper choice of control configuration for the selection of control variables, output variables, and outstanding controllers for this kind of process, since it involves multivariable interactions.

The multivariable predictive controllers addressed in [26] use fineness and elevator current as process variables, and the feed flow rate and separator speed as the control variables. The measurement of online fineness in the cement plant is rarely available. Process modelling is carried out based on the offline analysis of fineness in the laboratories [22]. In this study, the elevator current, which is a measure of fineness, is taken as one of the controlled variables, and the main drive load, which ensures the mill running, is taken as the other control variable. Separator speed is considered as one of the manipulating variables in the literature [8–12,24–26], in which different controllers are designed for the cement ball mill grinding process. The difficulty in using separator speed as one of the manipulating inputs is its limited efficient operating range. The separation becomes inefficient beyond 75% of the maximum speed, and hence if clinkers with a larger hardness enter the separator, the separation of coarse and fine particles becomes poor and deteriorates the product quality. Thus, the separator power is taken as one of the manipulating variables along with feed as another manipulating input, and the separator speed reaches its saturation. The process is modelled based on these controlled and manipulated variables.

The state-space model obtained using the subspace identification technique, as discussed in [34]; the corresponding state; and the input and output matrices are used to design the predictive controller, which is shown in Appendix A.

3. Predictive Controller Design

The schematic of the predictive controller is shown in Figure 3. The main controller block includes the model of the cement grinding process, the optimiser, and the objective function. The grindability variations are introduced into the cement grinding mill by incorporating the controller. The literature review in the introduction part indicates that the state-space-based model predictive controllers designed for the industrial processes have shown better set point tracking and disturbance rejection, and hence this research work focuses on the design of the SMPC controller for the cement ball mill grinding process. In industries, the physical constraints on the input manipulations and the rate of change of manipulations not only ensure the wear and tear of the equipment, but also the reduced energy consumption. The constraint handling capability of the predictive controllers make it suitable for any industrial processes. For this ball mill grinding process, to ensure energy optimization the physical constraints on the maximum and minimum outputs—namely, the elevator current, main drive load, and control inputs (namely, the feed flow rate and separator power)—are addressed effectively in this predictive controller. The rate of change of constraints on the inputs are also addressed to ensure the wear and tear of the grinding unit. The predictive controller solves an optimization routine for every sampling instant over the length of the receding horizon. Among the N control moves calculated, only the first control move is implemented in the control law. Since the computation is conducted online, it takes a considerable amount of time to solve this optimization routine. However, the state-space model-based predictive controller reduces the complexity compared to that of its counterpart transfer function model. The prediction matrices and the required control law for the cement ball mill grinding circuit are derived as follows, which is suggested in [35].



IE_ref	Elevator current—set point.	Np	Prediction horizon.
Pm_ref	Main drive load—set point.	Nc	Control horizon.
IE	Elevator current—actual.	e	Error between the setpoint and actual.
Pm	Main drive load—actual.	U	Manipulating inputs (feed flow rate and separator power).

Figure 3. Schematic diagram of the predictive controller implemented for the cement grinding process.

The one step ahead state prediction is given by:

$$x_{k+1} = Ax_k + Bu_k. \tag{1}$$

The multi-step ahead state prediction is given by:

$$x_{k+2} = Ax_{k+1} + Bu_{k+1} = A[Ax_k + Bu_k] + Bu_{k+1},$$

$$x_{k+3} = Ax_{k+2} + Bu_{k+2} = A([Ax_k + Bu_k] + Bu_{k+1}) + Bu_{k+2},$$

$$x_{k+4} = Ax_{k+3} + Bu_{k+3} = A(A([Ax_k + Bu_k] + Bu_{k+1}) + Bu_{k+2}) + Bu_{k+3}.$$

Expanding this results in the following equations:

$$x_{k+1} = Ax_k + Bu_k,$$

$$x_{k+2} = A^2x_k + ABu_k + Bu_{k+1},$$

$$x_{k+3} = A^3x_k + A^2Bu_k + ABu_{k+1} + Bu_{k+2},$$

$$x_{k+4} = A^4x_k + A^3Bu_k + A^2Bu_{k+1} + ABu_{k+2} + ABu_k.$$

The general expression for the n-step ahead prediction is given by:

$$x_{k+n} = A^nx_k + A^{n-1}Bu_k + A^{n-2}Bu_{k+1} + \cdots + ABu_{k+n-2} + Bu_{k+n-1}. \tag{2}$$

The output equation for the n-step ahead prediction is determined as:

$$y_{k+n} = Cx_{k+n} + d_{k+n}, \tag{3}$$

$$y_{k+n} = CA^n x_k + C\left(A^{n-1}Bu_k + A^{n-2}Bu_{k+1} + \cdots + ABu_{k+n-2} + Bu_{k+n-1}\right) + d_k. \tag{4}$$

In the above Equation (4), d_{k+n} is approximated to d_k, since the disturbance is slowly varying in nature for the cement ball mill grinding process. The n-step ahead state prediction is written in matrix form as below:

$$\underset{\rightarrow k+1}{x} = \underbrace{\begin{bmatrix} A \\ A^2 \\ \vdots \\ A^n \end{bmatrix}}_{P_x} x_k + \underbrace{\begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{n-1}B & A^{n-2}B & \cdots & B \end{bmatrix}}_{H_x} \underbrace{\begin{bmatrix} u_k \\ u_{k+1} \\ \vdots \\ u_{k+n-1} \end{bmatrix}}_{\underset{\rightarrow}{u}}. \tag{5}$$

The vector notation of the state prediction equation in Equation (5) is written in compact form: as

$$\underset{\rightarrow k+1}{x} = P_x x_k + H_x \underset{\rightarrow k}{u}. \tag{6}$$

The output prediction for n-steps is written as in Equation (7):

$$\underset{\rightarrow k+1}{y} = \underbrace{\begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^n \end{bmatrix}}_{P} x_k + \underbrace{\begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{n-1}B & CA^{n-2}B & \cdots & CB \end{bmatrix}}_{H} \underbrace{\begin{bmatrix} u_k \\ u_{k+1} \\ \vdots \\ u_{k+n-1} \end{bmatrix}}_{\underset{\rightarrow}{u}}. \tag{7}$$

Similar to Equation (6), the vector notation of output prediction Equation (7) is expressed as:

$$\underset{\rightarrow k+1}{y} = Px_k + H\underset{\rightarrow k}{u}. \tag{8}$$

The state and output predictions are shown in Equations (6) and (8).

The objective function J to be minimised is given by:

$$J = \sum\nolimits_{k=0}^{n} \left(e_{k+1}^2 + \lambda\left(u_k - u_{ss}\right)^2\right). \tag{9}$$

The deviations in the input variable $u_k - u_{ss}$ from the steady-state value u_{ss} ensure the unbiased prediction. The error term in the Equation (9) is expressed as $e_{k+1} = r_{k+1} - y_{k+1}$, where r_{k+1} is the setpoint, y_{k+1} is the output, and λ is the tuning factor.

The objective function is further modified by introducing the weighting matrices Q and R, and is given as:

$$J = \underset{\rightarrow k+1}{e^T} Q \underset{\rightarrow k+1}{e} + (\underset{\rightarrow k}{\hat{u}})^T R (\underset{\rightarrow k}{\hat{u}}), \tag{10}$$

where $\underset{\rightarrow k}{\hat{u}} = u_k - u_{ss} \underset{\rightarrow k}{\hat{u}} = u_k - u_{ss}$.

The constraints introduced in the controller design are shown from Equations (11)–(13):

$$U_{k-min} \le U_k \le U_{k-max}, \tag{11}$$

$$Y_{k-min} \le Y_k \le Y_{k-max}, \tag{12}$$

$$\Delta U_{k-min} \le \Delta U_k \le \Delta U_{k-max}. \tag{13}$$

Equation (11) is the constraints on the input manipulations (the feed and sepax power), Equation (12) is the constraints on the output variables (the elevator current and mill load), and Equation (13) is the constraints on the change in input manipulations.

The objective function is written as shown in Equation (14) by substituting Equation (8) into Equation (10):

$$J = [P_x \hat{x}_k + H_x \underset{\rightarrow k}{\hat{u}}]^T Q [P_x \hat{x}_k + H_x \underset{\rightarrow k}{\hat{u}}] + (\underset{\rightarrow k}{\hat{u}})^T R (\underset{\rightarrow k}{\hat{u}}). \tag{14}$$

The control law is obtained by taking the partial derivative of the equation with respect to $\hat{u}_k$ and equating it to zero. The required control law obtained is shown in Equation (15):

$$\hat{u}_k = [H_x{}^T Q H_x + R]^{-1} H_x{}^T Q P_x \hat{x}_k, \tag{15}$$

$$[H_x{}^T Q H_x + R]^{-1} H_x{}^T Q P_x. \tag{16}$$

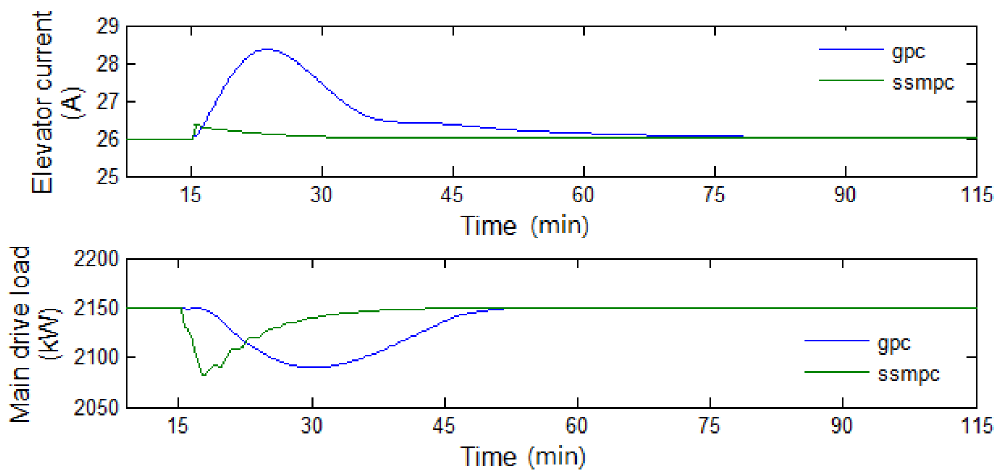
Equation (15) is of the form of state feed-back control law expressed as $\hat{u}_k = -K\hat{x}_k$, where the state feed-back gain K is given in Equation (16).

The control law obtained in Equation (15) is introduced into the cement ball mill grinding process to optimise the plant for the desired product quality and productivity under larger variations in the grindability factor.

4. Results and Discussion

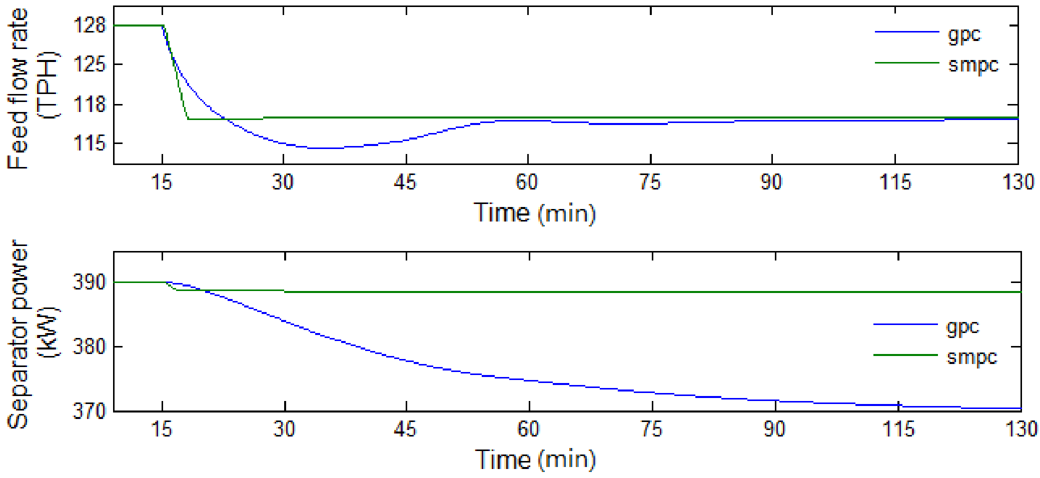
4.1. Performance of Predictive Controllers in Simulation

The SSMPC designed in this work is simulated in the cement mill model and compared with the GPC designed in [29] by Venkatesh et al. Since this investigation aims to maintain the product quality and productivity even in the presence of larger variations in the grindability factor of the clinker, the regulatory response of both the controllers is analysed by introducing a unit step change in the grindability factor at the 15th minute. The nominal value of the elevator current (an indirect measure of fineness) which maintains the desired fineness is affected and starts to increase. However, the predictive controller acts on the process to bring it to the nominal value again to achieve the desired fineness after transients, as shown in Figure 4. Figure 4a,b show the variations in the process-manipulating variables, respectively.



(**a**) Variations in the process variables—namely, the main drive load and elevator current.

Figure 4. *Cont.*



(**b**) Variations in the manipulating variables—namely, the feed flow rate and separator power.

Figure 4. (**a**) Variations in the process and (**b**) manipulating variables—namely, the main drive load, elevator current, feed flow rate, and separator power—on introducing different controllers viz. Generalized Predictive Controller (GPC) and State Space Model Predictive Controller (SSMPC).

It is evident from Figure 4a that GPC shows the highest peak in the elevator current compared to the SSMPC. On receiving the hard clinker, the mill runs at a lower speed and closer to the plugging phenomenon, however the controllers viz. GPC and SSMPC act on the system to maintain the main drive load to the nominal value, and hence the stability of the system is achieved by avoiding plugging. For both the controlled variables, viz. the elevator current and main drive load, the SSMPC results in a better performance in terms of the peak overshoot and settling time, which is also evident from Table 1. The peak value in the elevator current shows a larger value of 2.36 A in GPC compared with 0.37 A for SSMPC, which is 6.5 times less than that of the former controller. However, the main drive load shows almost similar peak values for both the controllers.

Table 1. Time-domain specifications and performance indices for different predictive controllers.

Sl.No	Output	Peak Time (min)	Settling Time (min)	Peak Overshoot	IAE	ISE	ITAE
GPC	Elevator Current	24	68	2.36 (A)	265.4960	380.1629	13,962.5
	Main drive load	30	51	60 (kW)	1158.22	5569	123,676
SSMPC	Elevator Current	12	30	0.37 (A)	43.9875	20.6775	2588.3
	Main drive load	12	21	67.4 (kW)	1841.82	72,583	1,156,675

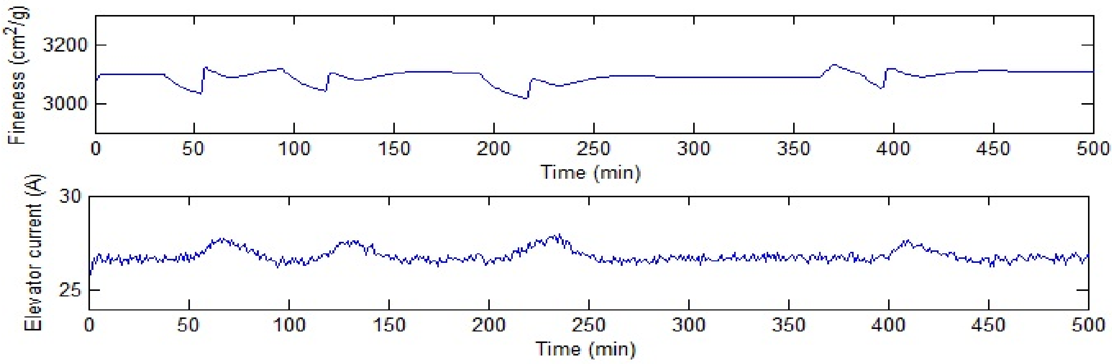
On clearly looking at Table 1, both the variables viz. the elevator current and main drive load almost take half of the time for settling to the nominal value for the SSMPC compared with GPC. The performance indices, such as integral absolute error (IAE), integral squared error (ISE), and integral time absolute error (ITAE), are analysed. It is evident from Table 1 that the SSMPC controller shows lesser values of IAE, ISE, and ITAE in comparison with GPC.

4.2. Performance of Controller in CEMulator

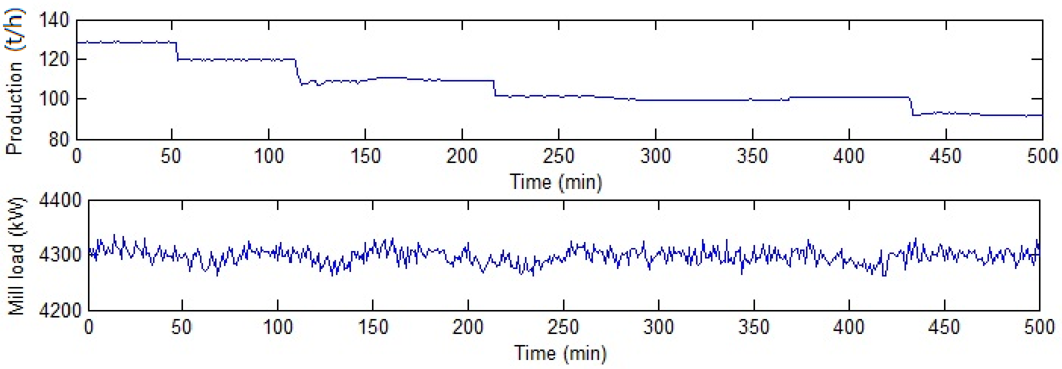
The performance of the designed predictive controllers is implemented and tested in the industrially recognised CEMulator, which is a real-time simulator with FLSmidth Pvt. Ltd., Cement and Minerals Projects India, Chennai. The nominal grindability factor for the clinker is 33, which is a dimensionless quantity. The grindability factor of the clinker is analysed in the laboratory. Harder clinkers have a lower grindability factor and vice versa. Different input and output process variables associated with the real-time simulator for the nominal value of grindability factor 33 is shown in Table 2. The GPC designed in [29] is implemented in the real-time simulator under the closed-loop condition which is shown in Figure 5. The hardness of the clinker is increased by varying the grindability factor of the clinker from 33 to 27 gradually at different time instances.

Table 2. Nominal values of the input and output variables in the real-time simulator for the clinker grindability factor of 33.

Sl.No	Variables	Nominal Value
01	Fineness	3100 cm^2/g
02	Elevator current	26 A
03	Production	127 TPH
04	Mill load	4347 kW
05	Feed	128 TPH
06	Sepax power	390 kW
07	Separator speed	70% (75 kW)

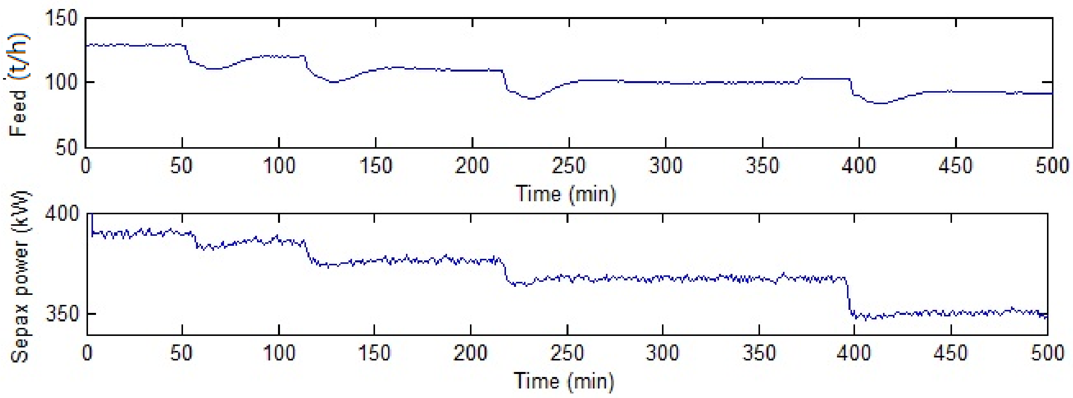


(**a**) Variation in the fineness and elevator current.



(**b**) Variation in the production and mill load.

Figure 5. *Cont.*



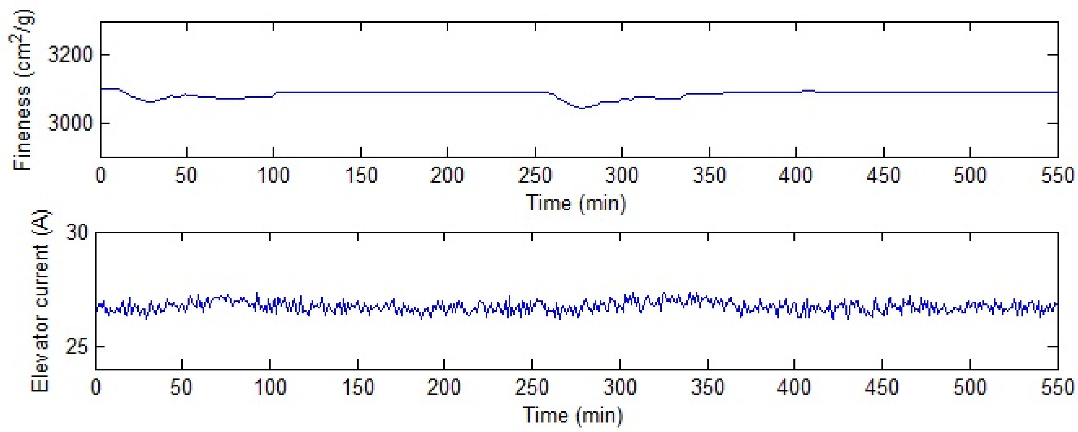
(**c**) Variations in the manipulating inputs.

Figure 5. Variations in the different process and manipulating variables when GPC is implemented in a real-time cement plant simulator.

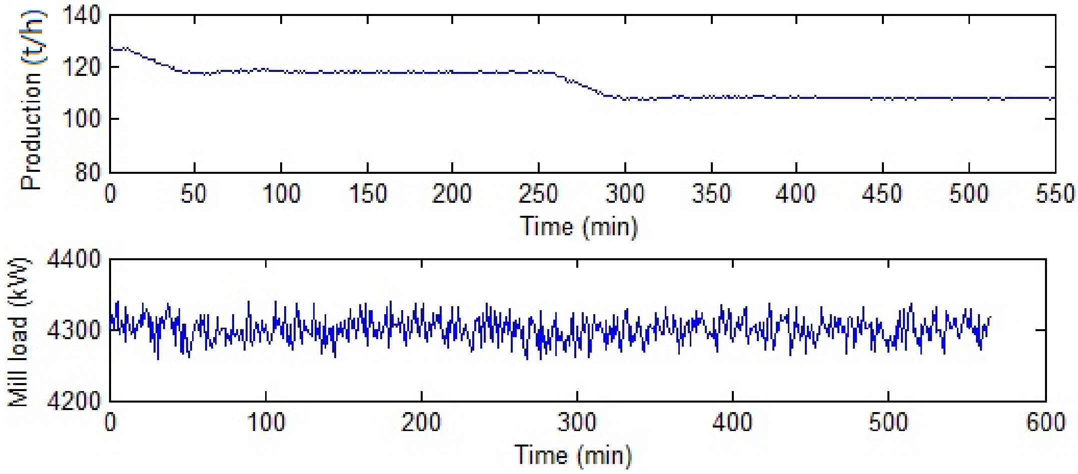
As shown in Figure 5a, at the 30th minute the clinker grindability factor is changed from 33 to 32; at the 90th minute from 32 to 30; at the 190th minute from 30 to 29; and, finally, at the 360th minute, the grindability factor is changed from 29 to 27. It is evident from Figure 5a that the fineness starts reducing from its nominal value of 3100 cm^2/g at the instance of lowering the grindability factor. At the same time, the elevator current, which is a measure of fineness, increases from its nominal value of 26 A to produce coarse cement particles at the outlet. However, the GPC controller acts on the process to maintain the fineness at the nominal value, which is evident from Figure 5a. The elevator current is also maintained at 26 A by the controller. On the other hand, as shown in Figure 5b the production output from the mill is reduced from the nominal value, which is obvious since the product quality (fineness) is maintained. The mill load is also maintained to its nominal after minimal fluctuations. The variations in the manipulating inputs viz. feed and sepax power are shown in Figure 5c.

The performance of the SSMPC is also tested under a closed-loop environment in the real-time simulator. The grindability factor of the clinker is changed from 33 to 30 at the 10th minute and from 30 to 27 at the 270th minute. The controller acts on the ball mill grinding process and maintains the product quality by bringing the fineness to its nominal value. On comparing the SSMPC with the GPC, the variations in the fineness and elevator current for GPC are significant in introducing grindability variations at regular intervals, which is evident from Figure 5a. However, the variations for SSMPC are very minimal, as shown in Figure 6a. Figure 6b shows the variation in the production and mill load for SSMPC. It is evident from Figure 6b that the mill load is maintained at its nominal value upon introducing SSMPC. In contrast, the GPC controller results in significant variations in the mill load. The changes in the input manipulating variables—namely, the feed flow rate and separator power—are shown in Figure 6c.

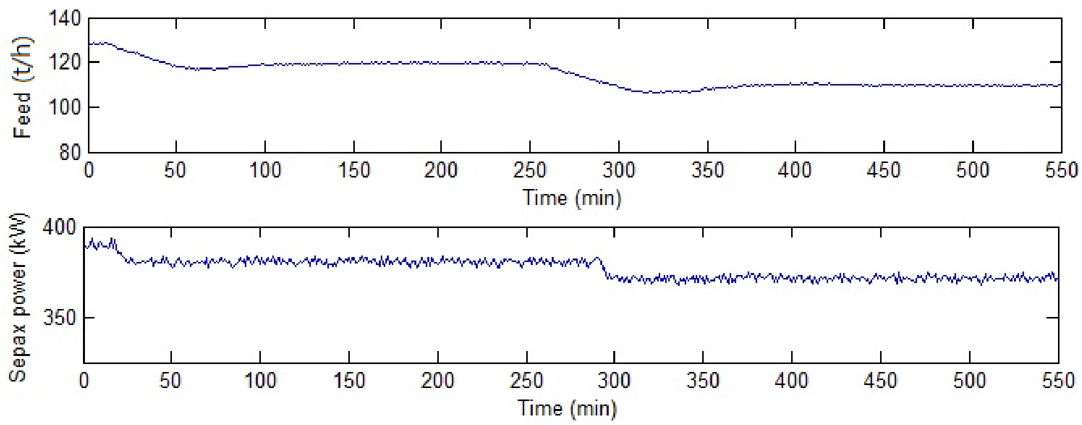
The existing controller designed in [26] is also tested in the real-time simulator under closed-loop conditions by changing the grindability factor of the clinker from 33 to 27 which is shown in Figure 7. On increasing the hardness of the clinker by changing the grindability factor from 33 to 30 at the 100th minute, the controller acts on the process to maintain the fineness and elevator current to the nominal value by changing the manipulating input feed and separator power, which is evident from Figure 7a,b, respectively. However, on further increasing the hardness of the clinker by changing the grindability factor from 30 to 27 at the 220th minute, the controller fails to maintain the fineness, since one of the manipulating inputs, separator speed, attains saturation, which is evident from Figure 7b. The mill load also reduces from its nominal value beyond the 300th minute and reaches a value closer to 3850 kW, as shown in Figure 7c, which may lead to the plugging phenomenon (obstruction of the mill) on further reduction in the mill load. On comparing the existing controller with the GPC implemented in the real-time simulator, GPC maintains the product quality and mill load at the nominal value in comparison with the existing controller designed in [26].



(**a**) Variations in the fineness and elevator current.

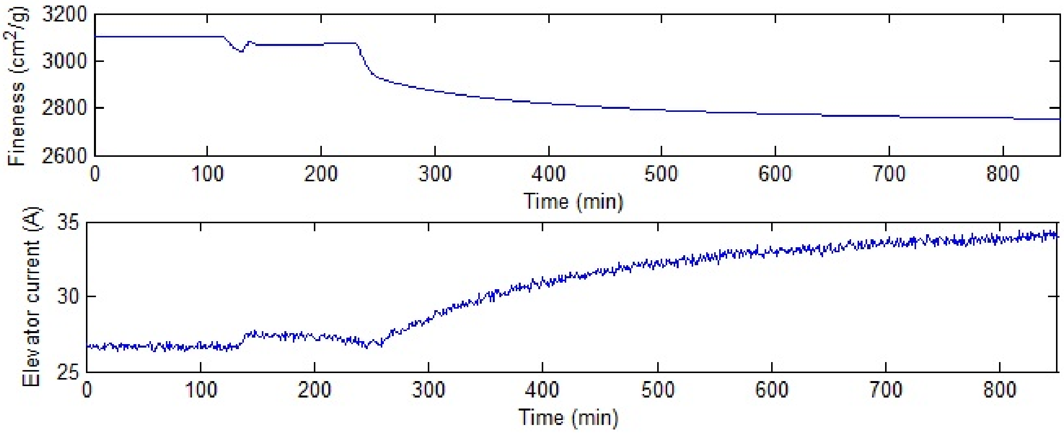


(**b**) Variations in the production and mill load.

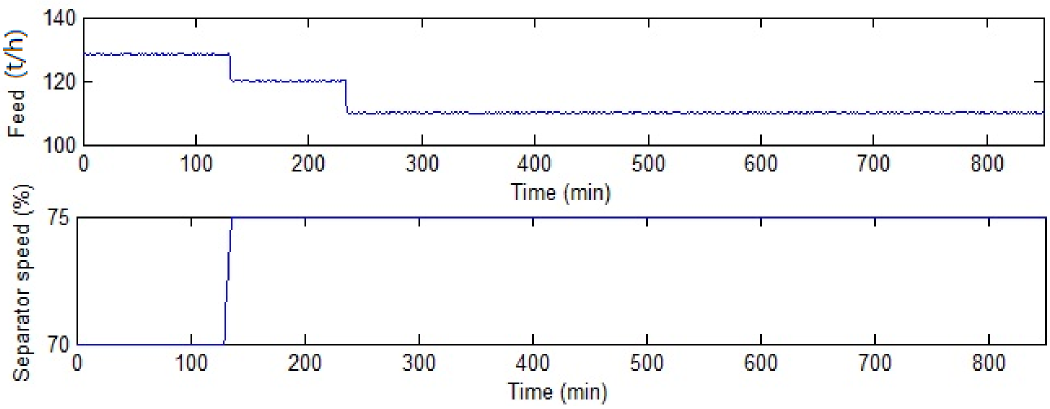


(**c**) Variations in the manipulating inputs.

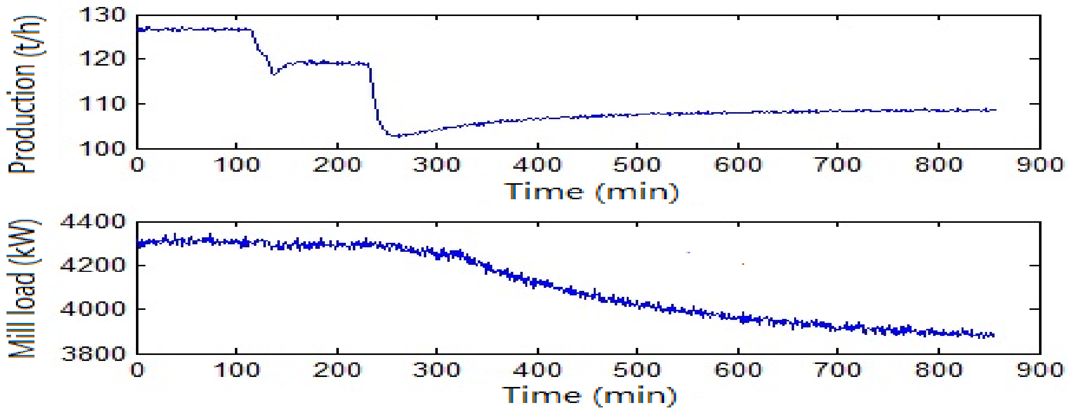
Figure 6. Variations in the different process and manipulating variables when SSMPC is implemented in the real-time cement plant simulator.



(**a**) Variations in the fineness and elevator current for an existing controller.



(**b**) Variation in the manipulating inputs for an existing controller.



(**c**) Variation in the production and mill load for the existing controller.

Figure 7. Variations in different process and manipulating variables in the presence of an existing controller in a real-time cement plant simulator.

To test the efficacy of the designed controller with their existing counterpart, the error performances indices such as the integral absolute error (IAE), integral squared error (ISE), and the integral time absolute error (ITAE) are analysed for the different controllers implemented under the closed-loop environment in the real-time simulator. Different process variables, viz. fineness, elevator current, production, and mill load, are analysed for error performance. SSMPC produces the lowest values of IAE, ISE, and ITAE for all the four process variables considered, resulting in a better performance than the other two controllers. For the fineness and elevator current, GPC results in error performance indices that are close to SSMPC but slightly larger than those of SSMPC, which is evident from Table 3.

Table 3. Error performance indices for the different controllers implemented in the real-time simulator under the closed-loop conditions.

Sl.No	Process Variables	IAE (×10^3)			ISE (×10^4)			ITAE (×10^6)		
		SSMPC	GPC	Existing	SSMPC	GPC	Existing	SSMPC	GPC	Existing
1	Fineness (cm^2/g)	7.616	7.910	75.852	17.923	23.82	1924.6	1.934	1.790	28.677
2	Elevator current (A)	0.117	0.127	0.996	0.004	0.006	0.038	0.033	0.029	0.395
3	Production (TPH)	7.830	39.654	6.707	12.513	31.259	12.799	2.666	9.449	2.311
4	Mill load (kW)	20.471	20.655	48.532	91.330	93.183	95.761	5.882	5.337	19.314

Since the fineness and elevator current are indicators of the product quality, lowering the values of the error metrics results in a better product quality. This is ensured in both the GPC and SSMPC. Considering the mill production, SSMPC and existing controllers produce lower values in the error performance indices; however, for the existing controller, IAE, ISE, and ITAE result in larger values for the fineness and elevator current, and hence a deterioration in the product quality. The error performance for the mill load also results in a larger value, which may lead to the plugging of the mill. However, GPC and SSMPC show a lesser value for the mill load compared with the existing controller, and hence cause the mill to run without stoppage.

From the above discussion, it is clear that both GPC and SSMPC produce a better performance in terms of error metrics compared to that of the existing controller. Among GPC and SSMPC, though GPC results in lower values in the error metrics for fineness, elevator current, and mill load, it does not result in a nominal value in production. However, SSMPC outperforms the other two controllers—namely, GPC and existing controller, in terms of product quality and productivity. SSMPC results in lesser values of error metrics for all the process variables viz. fineness, elevator current, production, and mill load, as shown in Table 3.

Other than error metrics, the performance of the different controllers is tested by analysing the variability in the process variables when the controller is implemented in the process under closed-loop conditions. Since the variations around the nominal value give a good measure of plant operation even in the presence of grindability variations, these variability metrics are analysed in this study. The lesser the variability, the better the performance of the controller. Table 4 shows the range and variability of the process variables when the controllers are implemented in the ball mill grinding process. It is evident from Table 4 that the fineness and elevator current result in a lesser variability for SSMPC compared with that of the other two controllers, and hence ensure the product quality. Considering the variability in production, SSMPC shows a lesser value compared to that of GPC, and hence the SSMPC outperforms the other two controllers in terms of its better product quality and productivity.

Table 4. Variability and range of process variables when different controllers are implemented under closed-loop conditions.

Process Variables	Range of Process Variables			Variability of Process Variables		
	SSMPC	GPC	Existing	SSMPC	GPC	Existing
Fineness (cm^2/g)	3040–3098	3017–3129	2755–3098	58	112	343
Elevator current (A)	26.19–27.32	25.81–27.97	26.51–34.19	1.13	2.16	7.68
Feed (TPH)	106.38–128.7	83.02–128.79	110.1–128.7	22.32	45.77	18.6
Sepax power (kW)	367.76–393.4	346.64–388.22	–	25.64	41.58	–
Mill load (kW)	4258–4340	4260–4336	3895–4298	82	76	403
Production (TPH)	107.17–127.19	91.57–127.5	102.8–126.8	20.02	35.93	24

In order to further enhance the efficacy of the SSMPC controller designed for the cement ball mill grinding process, the mean and variance of different process variables are analysed by comparing them with the nominal values. Table 5 shows the mean and variance of different process variables along with their nominal values when the ball mill is operating under normal conditions with a clinker grindability factor of 33. The mean and variance are calculated for the process variables when the mill is run by introducing the variations in clinker grindability. The means of the fineness and elevator current when implementing SSMPC and GPC are closer to the nominal values, and thus ensure the product quality. SSMPC shows a closer value of the mean to the nominal value for the production. However, GPC does not, and hence the productivity is improved in SSMPC compared to that of GPC. For mill load, GPC and SSMPC result in a mean value closer to the nominal value, and hence the mill is run without any obstruction. The existing controller fails to produce the mean for fineness, elevator current, and mill load, which is closer to the nominal, and hence its performance deteriorates in the presence of larger variations in the grindability factor of the clinker.

Table 5. Mean and variance of process variables by implementing different controllers in the closed loop.

Variable/Controller	Mean			Nominal Value	Variance		
	Existing	GPC	SSMPC		Existing	GPC	SSMPC
Fineness (cm^2/g)	2878	3091	3085	3099	17616	398	121.2
Production (TPH)	111.5	106.7	113.3	127	55.2	135.3	29.46
Mill load (kW)	4107	4297	4300	4347	26540	192.9	316.3
Elevator current (A)	30.53	26.8	26.7	26	7.91	0.113	0.059
Feed (TPH)	113.9	103.7	114.5	128	47.38	143.17	31.39

5. Conclusions

Controllers are necessary for the cement ball mill grinding process to automate the plant for providing less energy per unit production of cement. The plant under consideration is an indigenous grinding unit, for which the clinkers are procured from different vendors across the country, and hence their grindability factor varies to a larger extent. Grindability factor variations (i.e., the deciding factor of the hardness of the clinkers) in the clinkers are the key contributor in determining the product quality and productivity of the final cement product. Predictive controllers are widely accepted in industries because of their inherent properties, and hence are attempted for this indigenous grinding unit. The GPC is designed [25] based on the transfer function model obtained from the polynomial based Box Jenkins (BJ) model and its counterpart. In this work, SSMPC is designed using the state-space model. The predictive controllers are tested in the real-time simulator, the ECS/CEMulator at FLSmidth Pvt. Ltd., Chennai, under closed-loop conditions. This simulator provides a realistic environment similar to that of the plant. The grindability variations are introduced and varied to a large extent from the grindability factor of 27 to 39, with 33 being the nominal value. The responses are analysed with the existing, GPC [25], and SSMPC controllers. The GPC and SSMPC controllers are able to maintain the product quality irrespective of the variations in the grindability factor, whereas the existing controller fails to do so under large differences in the hardness of the clinkers.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The state-space model of the cement ball mill grinding process used in this process is having the following state (A), input (B) and output (C) matrices

$$A = \begin{bmatrix} 0.9800 & -0.0076 & -0.0514 & 0.0781 \\ 0.0093 & 0.9602 & 0.0870 & 0.0908 \\ 0.0079 & -0.0181 & 0.4516 & 1.1416 \\ -0.0243 & 0.0059 & -0.8578 & 0.2152 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.0001 & -0.0003 \\ -0.0003 & 0.0002 \\ -0.0004 & -0.0002 \\ 0.0014 & 0.0001 \end{bmatrix}$$

$$C = \begin{bmatrix} 54.3263 & 1.4986 & 3.6856 & -0.9473 \\ -105.9066 & 189.4945 & -34.0067 & -16.2345 \end{bmatrix}$$

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