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# Soft Constrained based MPC for Robust Control of a Cement Grinding Circuit

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**Abstract:** In this paper, we develop a novel Model Predictive Controller (MPC) based on soft output constraints for regulation of a cement mill circuit. The MPC is first tested using cement mill simulation software and then on a real plant. The model for the MPC is obtained from step response experiments in the real plant. Based on the experimental step responses an approximate transfer function model for the system is identified. The performance of the MPC in the real plant compares favorably to the existing control system based on fuzzy logic. Compared to the other controllers, soft MPC handles the real time uncertainties effectively. It also regulates the cement mill circuits better and in a plant friendly way by using less variation in the manipulated variables (MVs).

*Keywords:* Model Predictive Control; Cement Mill; Industrial Process Control

## 1. INTRODUCTION

The annual world consumption of cement is around 1.7 billion tons and is increasing at about 1% a year. The electrical energy consumed in the cement production is approximately 110 kWh/ton. Global cement production use approximately 2% of the worlds primary energy consumption and 5% of the total industrial energy consumption (Concil, 1995; Austin et al., 1984). 30% of the electrical energy is used for raw material crushing and grinding while around 40% of this energy is consumed for grinding clinker to cement powder (Fujimoto, 1993; Jankovic et al., 2004).

Clinker grinding can be done either using a ball mill or a vertical roller mill. It is the final stage in cement production where the clinker is ground with other materials to form fine cement powder. The ball mill is the most common process for cement grinding. The reasons are it high reliability, its possibility of gypsum dehydration and the easy maintenance of ball mills.

The ball mill, is designed for grinding of clinker, gypsum and dry or moist additives to produce any type of cement and for separate dry grinding of similar materials with moderate moisture content. All mill types may operate in either open or closed circuit and with or without pre-grinder, to achieve maximum overall grinding efficiency and high flexibility in terms of product quality. Fig. 1 shows a typical layout of the mill. Usually ball mills are divided into two chambers depending on the size of the input material used and the availability of a clinker pre-grinding circuit. Up to 5% gypsum and/or natural anhydrite is added to regulate the setting time of the cement. Other chemicals, such as those which regulate flow or air entrainment, may also be added. Fine grinding using ball mills is in general extremely energy inefficient. Many plants use a roll crusher to achieve a preliminary size reduction of the clinker and gypsum. Just 4% of the energy available is efficiently used for grinding.

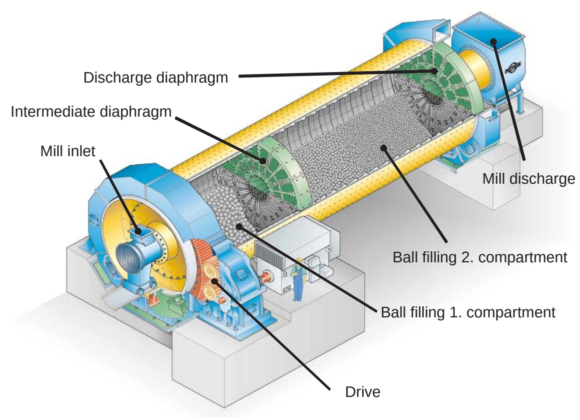


Fig. 1. Ball mill layout

Efficient control is required in order to reduce the specific production costs while maintaining the product quality at an acceptable level. The control philosophy for cement mill thus remains challenging as low production results in huge power consumption and high production may cause inefficient grinding. The cement grinding controller must provide economically efficient production which is

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equivalent to delivery of a consistent on target product quality with minimal power consumption.

Conventionally, the grinding circuits are controlled by multi-loop PID controllers and linear predictive controllers (Chen et al., 2008). The uncertainties in the linear predictive model of the cement mill circuit stems from large variations and heterogeneities in the feed material as well as operational variations. These sources of variations give rise to nonlinear behavior and variations in the dead-times of the cement mill circuit. The models are obtained from step response experiments conducted on the cement mill circuit. The uncertainties may be characterized by the gains, time constants, and time delays in a transfer function model. To control such circuits, we propose a MPC that uses soft constraints (soft MPC) to robustly address the large uncertainties present in models that can be identified for cement mill circuits (Prasath and Jørgensen, 2009; Prasath et al., 2010).

The developed soft MPC is compared to a normal MPC on the ECS/Cemulator (Prasath et al., 2010). In this paper, we provide the details on the implementation of soft constrained MPC on a real cement grinding circuit and compare its performance to the existing fuzzy logic based control system.

This paper is organized as follows. The principle of predictive controller consisting of a regulator and an estimator with soft output constraints is described in section 2. Section 3 gives the details of model identification and the comparison of soft MPC with fuzzy logic controller in a real cement milling process and the results are discussed from the plots. Conclusions are given in Section 4.

## 2. SOFT MPC ALGORITHM

The principle of soft MPC algorithm used to control the cement mill circuit is discussed in Prasath and Jørgensen (2009). The cost function is formulated as a regularized $\ell_2$ output tracking problem with input and soft output constraints as given in (1a).

$$\min_{\{z,u,\eta\}} \phi = \frac{1}{2}\sum_{k=0}^{N-1} \|z_{k+1} - r_{k+1}\|_{Q_z}^2 + \|\Delta u_k\|_S^2 + \sum_{k=1}^{N} \frac{1}{2}\|\eta_k\|_{S_\eta}^2 + s_\eta' \eta_k \tag{1a}$$

subject to the constraints

$$z_k = b_k + \sum_{i=1}^{n} H_i u_{k-i} \qquad k = 1, \dots N \tag{1b}$$

$$u_{\min} \le u_k \le u_{\max} \qquad k = 0, \dots N-1 \tag{1c}$$

$$\Delta u_{\min} \le \Delta u_k \le \Delta u_{\max} \qquad k = 0, \dots N-1 \tag{1d}$$

$$z_k \le z_{\max,k} + \eta_k \qquad k = 1, \dots N \tag{1e}$$

$$z_k \ge z_{\min,k} - \eta_k \qquad k = 1, \dots N \tag{1f}$$

$$\eta_k \ge 0 \qquad k = 1, \dots N \tag{1g}$$

in which $\Delta u_k = u_k - u_{k-1}$.

The output predictions used by the regulator are generated based on the finite impulse response coefficients extracted from the model. To have offset free steady state control when unknown step disturbances occur, we include a integrator feedback loop to the controller (Prasath and Jørgensen, 2009).

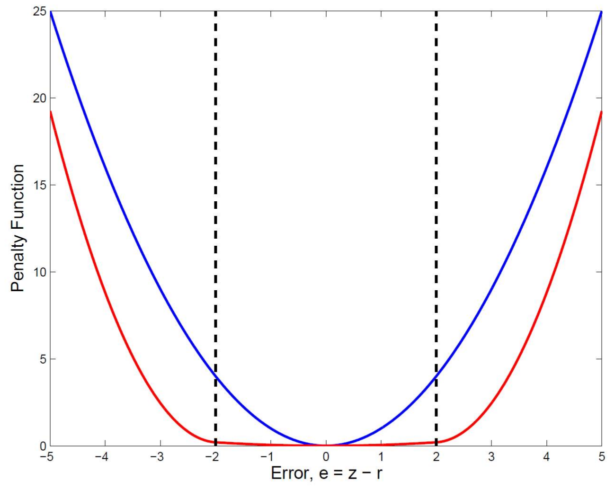


Fig. 2. Penalty function for soft MPC (red) and normal MPC (blue).

The objective function with input and soft output constraints is converted into a dense quadratic program which can be solved efficiently. The cost function and the solution of the quadratic program are discussed by Prasath and Jørgensen (2008, 2009). The feedback loop to the given controller is a simple integrator based on the FIR models obtained to add as a simple bias to the estimator. Here we make an assumption that the disturbances enter the controller as constant output disturbances. The values of $z_{\min,k} - \eta_k$ and $z_{\max,k} + \eta_k$ are determined based on variance of the noise in each measurements. Figure 2 illustrates the basic principle of soft constrained based MPC (soft MPC). The soft MPC provides one way to detune the controller such that it can handle the significant uncertainties in the process. The main difference between the normal MPC and the soft MPC is that the penalty function of the normal MPC is quadratic whereas the penalty function of the soft MPC is constructed such that it is zero or almost zero within the dead-zone between the soft limits and grows quadratically when the set-point error exceeds the soft limits. The small penalty within the soft limits ensures that the controller produces a steady state offset free response. Also the small penalty within the limits makes the controller react only a little to small variations in the measurements.

## 3. SYSTEM IMPLEMENTATION

The developed soft MPC is initially implemented for the ECS/CEMulator. The ECS/Cemulator is a rigorous cement plant simulator that is normally used for operator training and can also used as a realistic surrogate for a real cement mill for comparing different controllers by creating similar operating conditions. Prasath et al. (2010) provides a comparison of the soft MPC and the normal MPC using the ECS/Simulator. In this paper, the soft MPC is tested in a real cement mill and compared with that of the existing high level controller based on the fuzzy logic principle. The main difference in controlling the cement mill in the CEMulator and the real plant is that the CEMulator has uncertainty and noise defined by

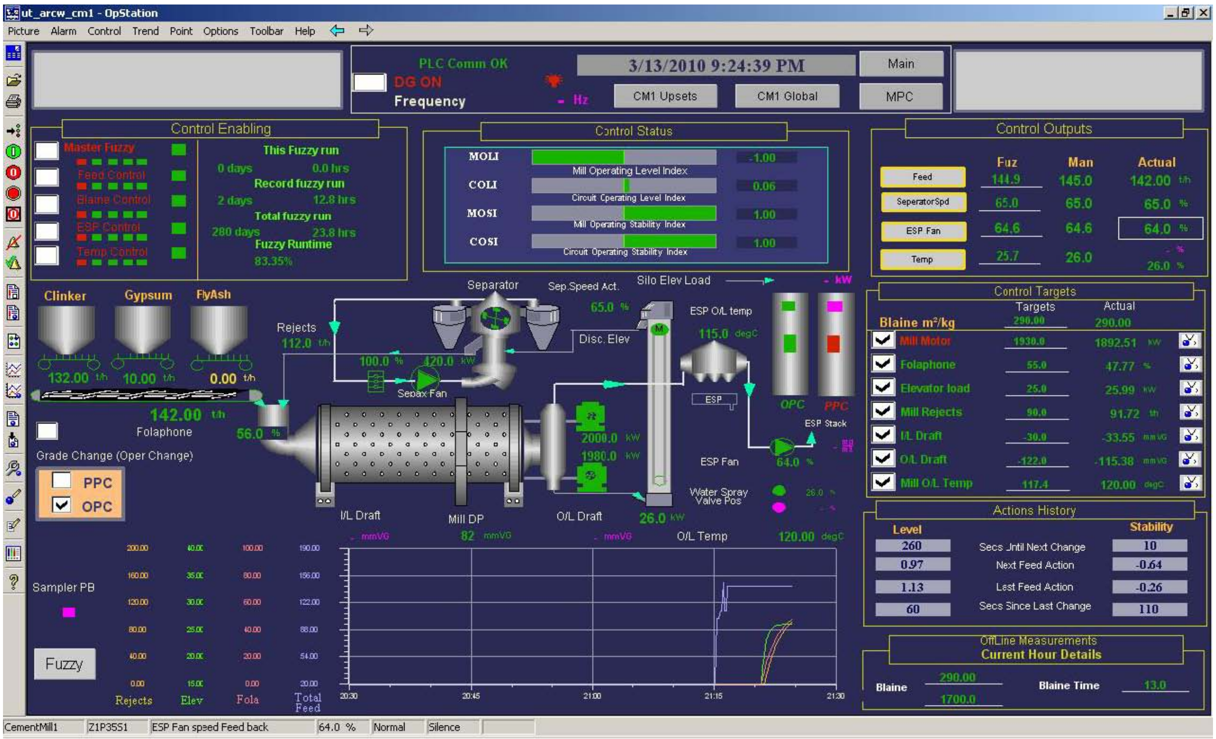


Fig. 3. Typical operator station of a cement mill controller

the user and operates the same way all the time. The CEMulator is based on a first principle models of the process and mechanical conditions. The real plant has a number of significant uncertainties to be handled because of raw material variations, wear and tear of mechanical devices etc.

The plant where we implement the controllers is an independent grinding unit. The major raw material clinker is obtained from plants from different parts of India and transported through railway wagons. The cement mill present in the plant is a closed circuit ball mill with two chambers. The cement ball mill has a design capacity of 150 tonnes/hour with a sepax separator. The separator can be varied around 70% to have better efficiency. The recirculation ratio of the circuit is 1.5%. The final product types are Ordinary Portland Cement (OPC) and Puzzalona Portland cement (PPC). The difference between OPC and PPC is that in PPC, fly-ash is added as one of the raw material to improve the fineness of the cement. Thus the production level and the operating range is different for OPC and PPC. A typical operator station for the cement mill circuit is shown in Figure 3.

All the signals coming from the sensors of the grinding process are collected in an ECS SCADA (Supervisory Control And Data Acquisition of FLSmidth) system. The measurement data is obtained from a PLC and logged every 10 seconds in the system. The quality measurement data (fineness/blaine) is entered every hour as an off-line measurement using the samples collected through an auto-sampling system.

The real time implementation of the soft MPC application is done using a high level expert system tool developed by FLSmidth. The execution interval of MPC will be 1 min and the data update in the expert tool will be 30 seconds.

The normal running range of the elevator load is from 20 kW to 35 kW for obtaining blaine of 300 $cm^2/g$. The fuzzy calculation engine executes every 30 seconds. The controller actions can be shifted from Fuzzy to MPC and vice-versa using a software switch. The measurement data obtained from the PLC through input/output modules in the field is filtered, scaled and validated before used in the controller. The output from the controller is also scaled and configured for bump less transfer when it is made online. This is important in order to have smoother transition of set points when the controller is shifted from manual to auto control loop. Interlocks are included in case of emergency shut down during abnormal conditions like power failure, feed starvation etc.

### *3.1 Model Identification*

The models of the system are identified in open-loop by doing step response tests. The general principle in the model construction phase is to stabilize the system around its desired operating point and then perturb the system with a step change of each of the process inputs. The responses of the output (measurement) variables are recorded. The process inputs must be perturbed individually. By the data obtained using this procedure, a model describing the influence of the process inputs on the process outputs can be constructed. The controller uses this model for computation of the control actions. From Figure 4, it is evident that the model obtained using step response tests are quite uncertain. Thus when these models are used for designing the controller, the performance of the controller degrades because of uncertainties in the model (Prasath and Jørgensen, 2008).

The feed and separator speed are perturbed individually and the possible output values are measured and logged.

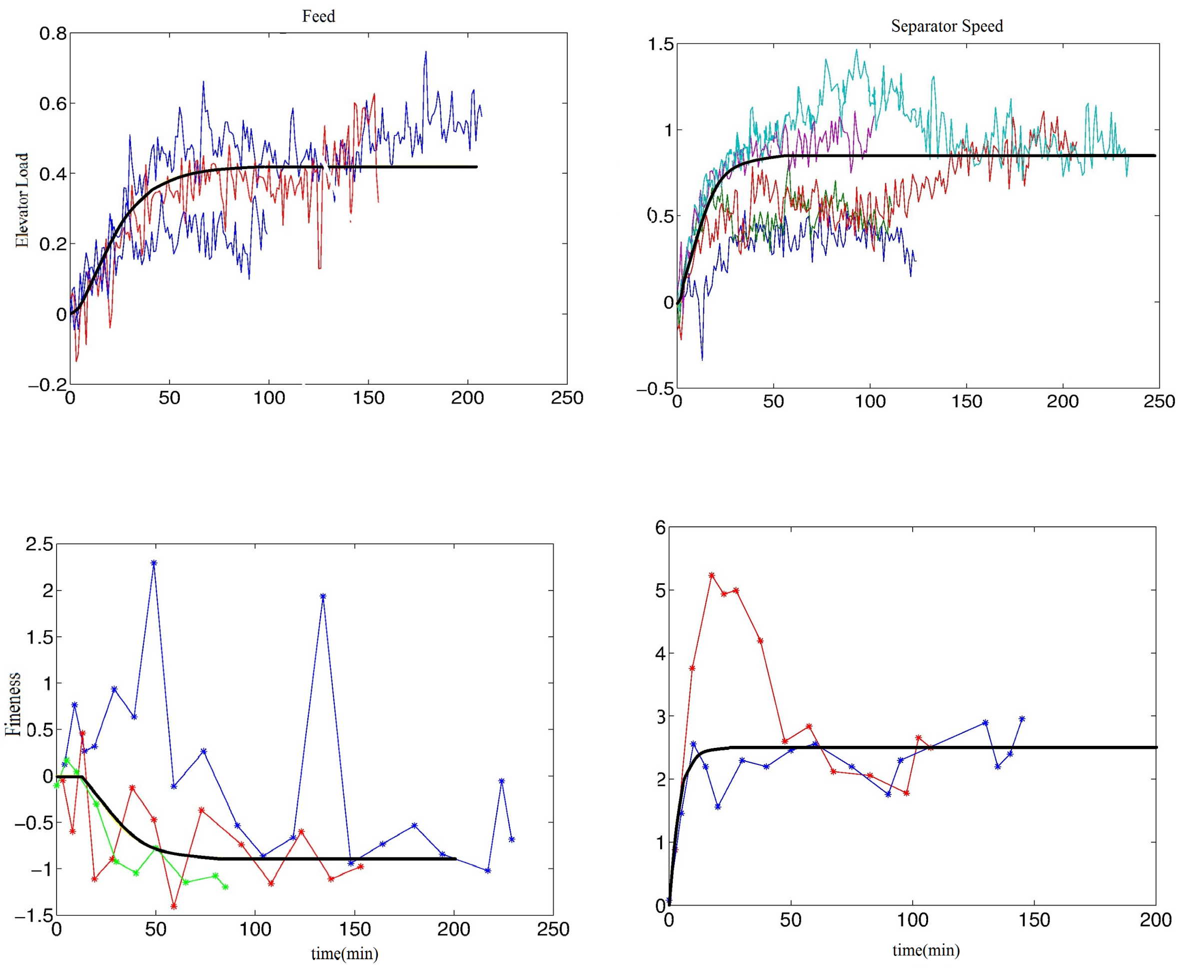


Fig. 4. Model identification using plant data from step response tests. The model identified is indicated by a solid black line. The other lines indicate plant data obtained from step response tests.

The lab measurement (fineness) is modeled by increasing the frequency of sample collection i.e., collecting samples for every 15 min and then generating a model based on the data.

We consider $2 \times 2$ MPC controllers based on the models Y (s) = G(s)U(s) with Y (s) = [Elevator Load; Fineness] and U(s) = [Feed; Separator Speed]. Based on the plots from the step experiments as shown in Fig. 4, we identify the system transfer function

$$G(s) = \begin{bmatrix} \frac{(0.47)(2s+1)}{(17s+1)(15s+1)}e^{-4s} & \frac{1}{12s+1}e^{-3s} \\ \frac{(-0.9)}{(10s+1)(12s+1)}e^{-5s} & \frac{2.5}{(4s+1)} \end{bmatrix} \quad (2)$$

### *3.2 Controller Performance Comparison*

Since the source of raw material for grinding is obtained from different regions, the physical and chemical properties of the clinker are different for each batch of the clinker used. This varies the grinding pattern for each of the clinker types and impacts the grinding efficiency of the cement mill. Hence the operating region of the parameters in the mill shifts continuously. To compensate for the quality variations in the feed material, we include target adaptation using a real time optimizer over the controllers. This helps in deciding the optimum operating range of the mill for improving the grinding efficiency. The elevator load is the parameter for control and so the target of elevator load is changed periodically depending on the quality of the final product. This helps to achieve optimum production while achieving the desired fineness.The controller varies the feed and separator speed to maintain elevator load and fineness.

The frequent power restrictions in the plant do not allow to run the cement mill more than 16 hours in a day. Normally the plant runs during the night, when the external electricity demand is low, and is stopped during the day. Mostly, the cement mill produces PPC as the main product. Also based on the demand, the cement plant may decide to run with OPC product for $3 - 4$ hours. Hence, we normally get only $12 - 15$ hours of continuous mill run to test our controllers. Depending on the dispatch requirements, sometimes the plant will be deciding on the type of cement to be produced for the particular day resulting in frequent shifting of operating points for the controller.

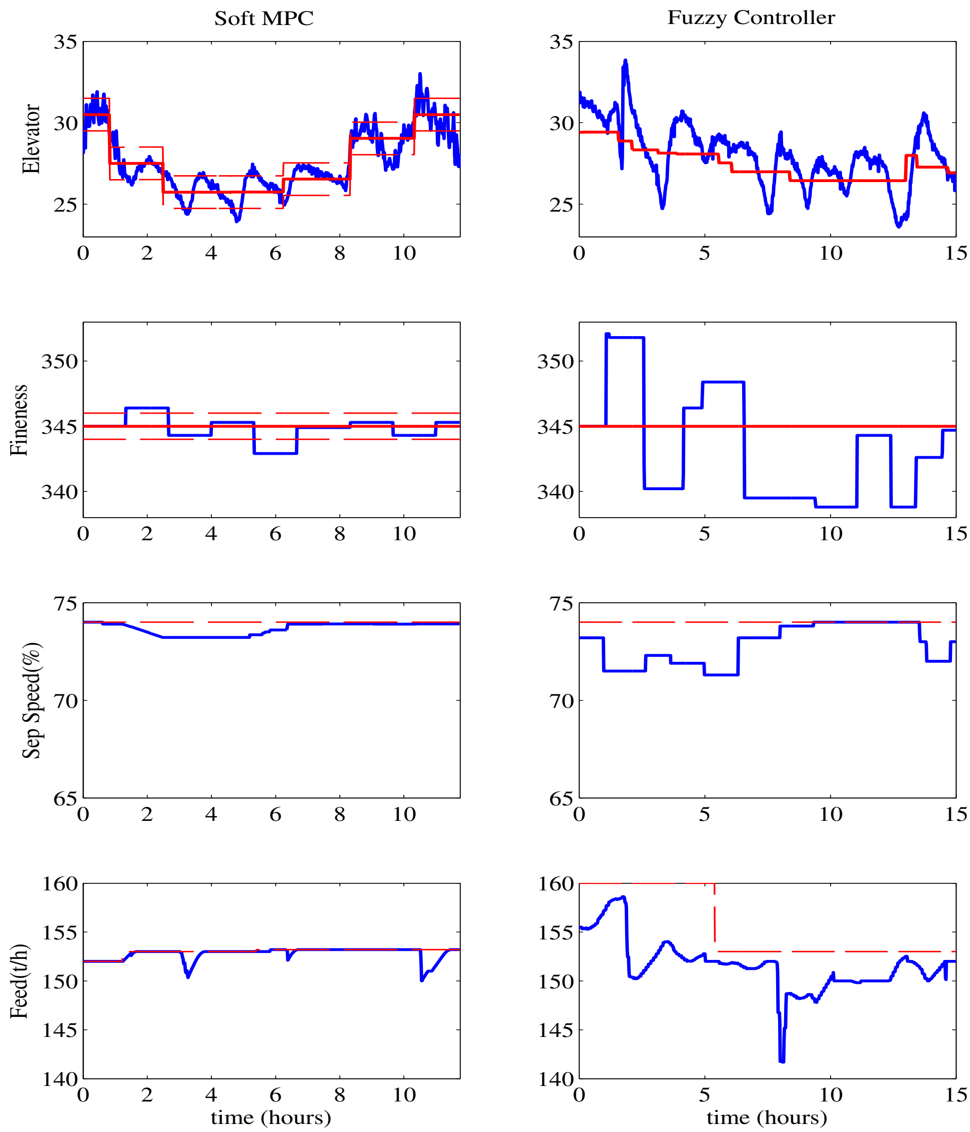


Fig. 5. Comparison of soft MPC with the fuzzy logic controller for a cement grinding circuit. The controlled variables are elevator (denotes the elevator load in kW) and fineness ($cm^2/g$) and the manipulated variables are feed (tph) and separator speed (%). The red line indicates the reference targets in measurements and blue line indicates the actual values. The dotted lines denote limits for both actuators and measurements

To have a common platform for comparison of the fuzzy logic controller and the soft MPC, both controllers are made online in similar operating conditions by running the controllers with the same source of clinker. This helps us to have a fair comparison of the controllers with similar material properties and it is quite easy to evaluate the performance based only on the process variations. The target adaptation based on operating range shift is also made available for both controllers.

First, the fuzzy controller is taken online for 15 hours and then the controller is switched to soft MPC for the next 12 hours. Both controllers are tested with the cement mill running continuously in a single recipe and producing Puzzalona Portland Cement(PPC). In PPC, gypsum, clinker and fly ash are the feed materials. This is to make sure that the controllers are compared in a fair basis with same operating conditions. It is confirmed that the fuzzy controller is perfectly tuned such that the soft MPC is tested against the best controller available in the plant. This is justified as the plant runs the fuzzy controller continuously whenever the mill is started and the plant personnel is quite satisfied with the performance of the fuzzy controller.

The following tuning and weighting factors are used while applying the soft MPC scheme to control the grinding circuit: Prediction- and control horizon $N = 300$, number of impulse response parameters $n = 100$. The tuning weights on the errors are $Q_z = [5 \times 10^{-2} \quad 0; 0 \quad 2.5 \times$

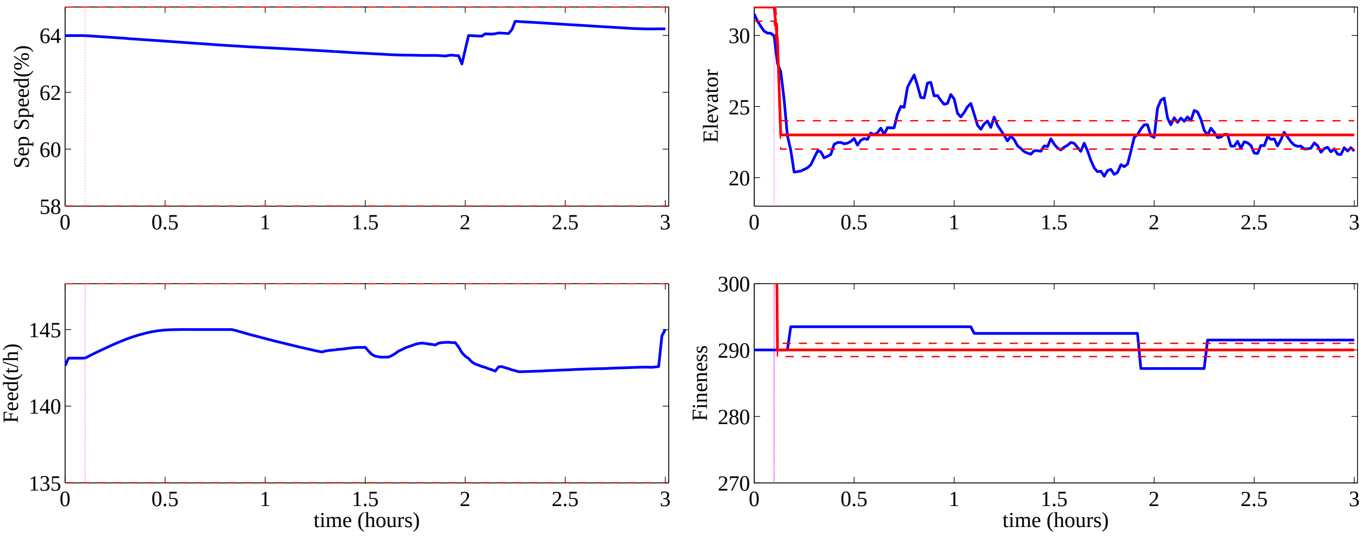


Fig. 6. Control variables (CVs) and actuator variations (MVs) with soft MPC running the controller online with OPC product. The pink line in the plot indicates the recipe change over and also the time when the controller is taken online

$10^{-5}$]; the tuning weights on the manipulated variables are $S = [5 \times 10^2 \;\; 0; 0 \;\; 2.5 \times 10^5]$; and the quadratic soft constraint tuning weights are $S_\eta = [9 \times 10^3 \;\; 0; 0 \;\; 5 \times 10^2]$. The sampling time $T_s = 1$ min. The linear soft constraint tuning weight is set to zero.

The tuning weight on the fineness is small compared to the tuning weight on elevator load; the fineness is an hourly sampled measurement and less accurate compared to elevator load. Also the weight on the separator speed is set to a large value because it is not permitted to move aggressively. This ensures a relatively stable operation.

From Fig. 5, we see that the soft MPC has the ability to control and stabilize the cement mill. The manipulated variables are smooth with the controlled variables are reasonably controlled. However it can be seen that the controller runs at its high limits and hence the actuator movements are restricted to move on the higher side. These conditions occur because of the conditions in the plant where there is inconsistency in quality variations of the raw material fed into the mill. Nevertheless, because of the limited variations in the separator speed, we observe that the standard deviation of the fineness has improved significantly for the soft MPC compared with the fuzzy logic controller.

Fig. 6 illustrates the performance of the soft MPC for a case where there is a large margin for the controller to adjust its actuator to maintain the desired target of controlled variables. The MPC algorithm uses soft constraints to create a piecewise quadratic penalty function in such a way that the closed loop system is less sensitive to model uncertainties. Thus the soft MPC moves the actuator very little within the soft constraints and takes aggressive actions outside the soft limit band resulting in smooth and stable operation of the cement mill circuit.

During the tests, it has been observed that the soft MPC handles operating point transitions better than the Fuzzy controller. In addition soft MPC reduces the quality variations (variations in fineness).

## 4. CONCLUSION

A controller with soft output constraints for handling the uncertainties of the cement mill circuit has been developed and implemented in a real cement grinding circuit plant. We implemented the controller in a real time cement plant to compare the performance of the controller with the existing Fuzzy controller running on the plant. The results indicate that the soft MPC handles the significant uncertainties efficiently and provides very good performance compared to other controllers.

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