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Application of Soft Constrained MPC to a Cement Mill Circuit

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Abstract: In this paper we develop a Model Predictive Controller (MPC) for regulation of a cement mill circuit. The MPC uses soft constraints (soft MPC) to robustly address the large uncertainties present in models that can be identified for cement mill circuits. 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 very nonlinear behavior and variations in the dead-times of the cement mill circuit. The uncertainties may be characterized by the gains, time constants, and time delays in a transfer function model. The developed soft MPC is compared to a normal MPC. The comparison is conducted using a rigorous cement mill circuit simulator used for operator training. The simulations reveal that compared to normal MPC, soft MPC regulate cement mill circuits better and in a plant friendly way by using less variations in the manipulated variables (MVs).

1. INTRODUCTION

The annual world consumption of cement is around 1.7 billion tonnes and is increasing at about 1% a year. The electrical energy consumed in the cement production is approximately 110 kWh/tonne. 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). Hence, global cement production uses 18.7 TWh which is approximately 2% of the worlds primary energy consumption and 5% of the total industrial energy consumption. The cement manufacturing process is illustrated in Fig. 1.

The final step in manufacture of cement consists of grinding cement clinker into cement powder. Ball mills are used for grinding the cement clinkers. The cement mill circuit consists of a ball mill and a separator. Fresh cement clinker and other materials such as gypsum and fly ash are fed to the ball mill along with recycle material from the separator. The ball mill crushes these materials into cement powder. This crushed material is transported to a separator that separates the fine particles from the coarse particles. The fine particles constitute the final cement product, while the coarse particles are recycled to the ball mill. These ball mills consume approximately 40% of the electricity used in a cement plant. Loading the cement mill too little results in early wear of the steel balls and a very high energy consumption per tonnes cement produced. Conversely, loading the mill too much results in inefficient grinding such that the product quality cannot be met. Cement quality is measured by its chemical composition and its particle size distribution. Blaine is an aggregate number for the particle size distribution measuring the specific surface area of the cement powder. Loading the cement mill too much, may even result in a phenomena called plugging such that the plant must be stopped and plugged material removed from the mill. Consequently, optimization and control of their operation is very important for running the cement plant efficiently, i.e. minimizing the specific electricity consumption and delivering consistent product quality meeting specifications. In this paper, we present new control technologies for operation of cement mill circuits. The improved operation resulting from these controllers can potentially lead to very large energy savings and at the same time provide a more consistent product quality.

We use a special Model Predictive Control (MPC) algorithm to control the cement mill circuit (Prasath and Jørgensen, 2009). This 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 than normal MPC with a quadratic penalty function. Predictive models for cement mills are very uncertain. Variations and heterogeneities of the cement clinker feed affects the gains, time constants, and time delays of the cement mill circuit. To avoid the MPC being turned off shortly after commissioning due to bad closed-loop behavior, it is important that these unmeasurable uncertainties are accounted for. The developed soft MPC controls the elevator power and the product Blaine (product quality) by manipulating the fresh feed flow rate and the separator speed. The elevator power can be measured in almost all cement mill circuits. Blaine can either be measured by online particle size analyzers or estimated using soft sensors. The models relating the manipulated variables to the controlled variables are identified from step response experiments on the cement mill circuit.

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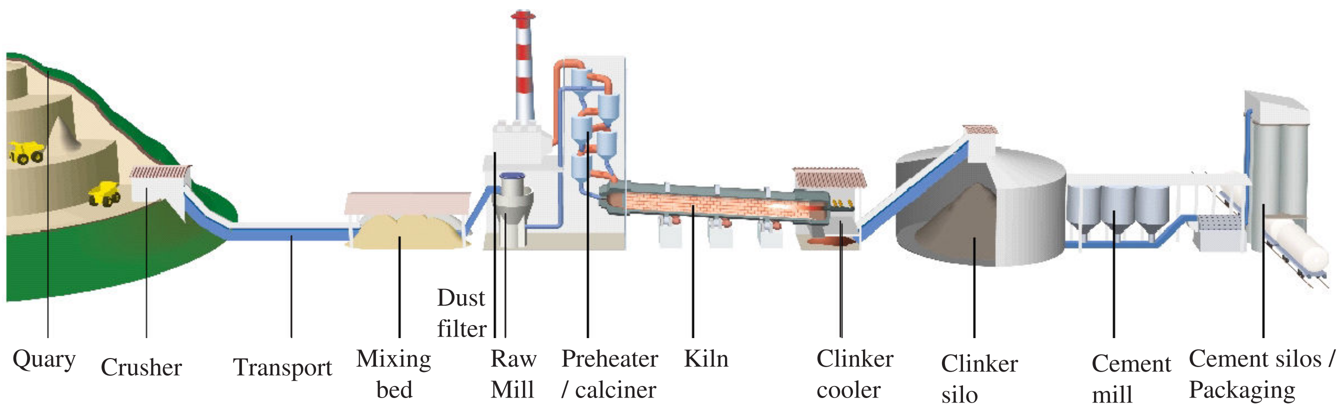

Fig. 1. Cement plant.

van Breusegem et al. (1994, 1996a,b) and de Haas et al. (1995) developed an LQG controller for the cement mill circuit. This controller was based on a first order 2×2 transfer function model identified from step response experiments. Magni and Wertz (1997), Magni et al. (1999), Wertz et al. (2000), and Grognard et al. (2001) developed a Nonlinear Model Predictive Control algorithm based on a lumped nonlinear model of the cement mill circuit. All these controllers controlled the product and recycle flow rate by manipulating the fresh feed flow rate and the separator speed. Efe and Kaynak (2002) used the same lumped nonlinear model for nonlinear model reference control. Lepore et al. (2002, 2003, 2004, 2007) as well as Boulvin et al. (1998, 1999, 2003) applied a distributed reduced order model for Nonlinear Model Predictive Control of a cement mill circuit. They controlled the particle size distribution of the cement product by manipulating the fresh feed flow rate and the separator speed. Martin and McGarel (2001) used a neural network model for Nonlinear Model Predictive Control of the cement mill circuit.

This paper is organized as follows. Section 2 describes the cement manufacturing process to provide the process context of a cement mill circuit. In this section, we also explain the cement mill circuit operating strategy. Section 3 reviews the soft MPC algorithm. Section 4 compares the Soft MPC to Normal MPC using a commercial rigorous cement mill circuit simulator. Conclusions are provided in Section 5.

2. CEMENT MANUFACTURING PROCESS

As illustrated in Fig. 1, the preparation of cement involves mining, crushing and grinding of raw materials (principally limestone and clay), calcining and sintering the materials in a rotary kiln to form clinker, cooling the resulting clinker, mixing the clinker with gypsum, grinding the clinker-gypsum mixture to cement powder, and storing and bagging the finished cement powder. The three main steps are 1) preparation of the raw mixtures, 2) production of the clinker, and 3) grinding the clinker into cement powder.

The raw materials used in cement production are limestone, sand, shale and iron ore. The main material, limestone, is normally mined on site while other materials may either be mined on site or in nearby quarries. These materials are crushed and screened to a size less than 100 mm. The crushed material is transported to the cement plant at which they are roughly blended in a pre-homogenization pile (mixing bed). The next step in the cement production depends on whether the wet or the dry process is used. In the wet process each material is proportioned to meet a desired chemical composition and fed to a rotating ball mill with water. The raw material is ground to a size where the majority of the material is less than 75 micron. The slurry is pumped to the blending tanks and homogenized to ensure that the chemical composition is correct. In the dry process, each raw material is proportioned to meet a desired chemical composition and fed to either a rotating ball mill or a vertical roller mill. The raw materials are dried with waste process gases and ground to a size where the majority of the material is less than 75 micron. The material from either type of mill is blended to ensure that the chemical composition is well homogenized. This so-called raw mix is stored in silos until required. This raw mix is a mixture of calcium carbonate, silicon-, alumina- and iron-oxides. Calcium and silicon are present to form strength producing calcium silicates. Aluminium and iron are present to produce liquid in the kiln burning zone. The liquid act as a solvent for the silicate forming reactions.

In the wet process, the slurry is fed to a rotary kiln. In the dry process the raw mix is fed to the preheater/calciner tower. The same basic physical and chemical process takes place in the kiln for the wet and the dry process. The raw mix is gradually heated by contact with the hot gases generated by combustion of the kiln feed. A number of chemical reactions take place as the temperature rises. At 70-110°C the water is evaporated. At 400-600°C clay like materials decompose into principally SiO_2 and Al_2O_3. Dolomite, $CaMg(CO_3)_2$, decomposes to $CaCO_3$, MgO and CO_2. At 650-900°C $CaCO_3$ reacts with SiO_2 to form belite, $2CaO{\cdot}SiO_2$. At 900-1050°C the remaining $CaCO_3$ decomposes to CaO and CO_2. At 1300-1450°C the material partial melts (20-30%), and belite reacts with CaO to form alite, $3CaO{\cdot}SiO_2$. Alite is the characteristic constituent of Portland cement. A peak temperature of 1400-1450°C is required to complete the reaction. The partial melting causes the material to aggregate into lumps or nodules with a typical diameter of 1-10 mm. This is called clinker. As the hot clinker leaves the kiln, they fall into a cooler that recovers most of the heat and cools the

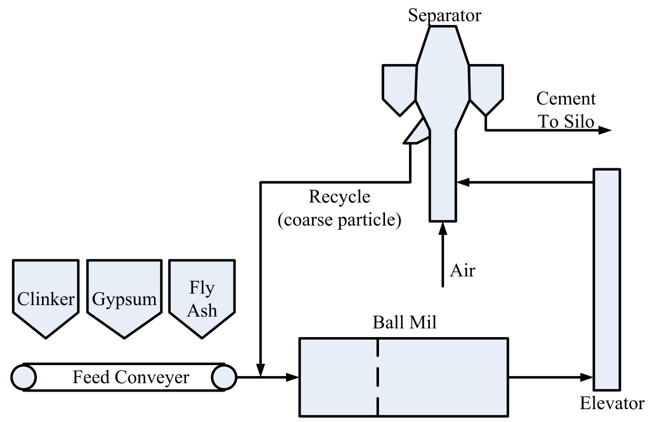

Fig. 2. Cement mill circuit.

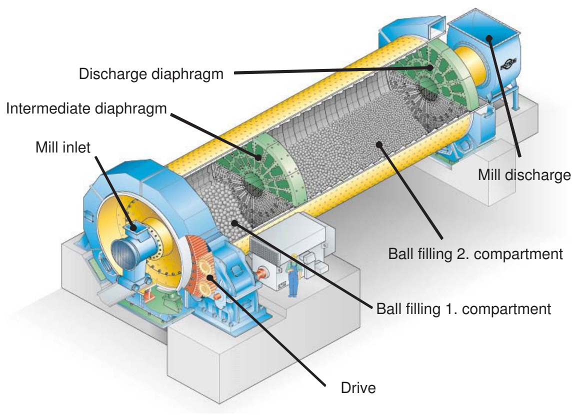

Fig. 3. Ball mill.

clinker to around 100°C. The clinker is stored in clinker silos.

In the final stage in the manufacture of cement, clinker is mixed with approximately 5% gypsum (calcium sulphate) and possible other materials such as fly ash and grinned to cement powder. Either a rotating ball mill or a vertical mill is used for grinding. In this paper we consider a rotating ball mill (Fig. 3). As the mill rotates, the steel balls inside the mill collide with clinker and raw material to form a fine gray powder. Typically, by mass 15% of the particles in this cement powder have a diameter less than 5 μm and 5% of the particles have a diameter larger than 45 μm. The specific surface area (Blaine) is usually used to measure the fineness of the cement powder as it is directly related to the properties of cement. General purpose cement has a specific surface area of 3200-3800 cm^2/g, while rapid hardening cement has a specific surface area of 4500-6500 cm^2/g. The various cement qualities are stored in cement silos before being packed in bags or shipped by truck, rail or boat.

2.1 Cement Mill Circuit

To obtain a cement powder with the desired specific surface area, the ball mill is operated in conjunction with a separator that returns coarse material to the ball mill for further grinding. This is called a cement mill circuit and is illustrated in Fig. 2. As illustrated in Fig. 3, the ball mills used for grinding have two chambers separated by a metallic diaphragm. The first chamber is filled with large steel balls and is supposed to do the coarse grinding. The second chamber is the fine grinding chamber and is equipped with small steel balls. Both chambers are equipped with classifying liners to ensure that the ball charge segregate with large balls accumulating at the inlet of the chamber and small balls accumulating at the outlet of the chamber.

The fine ground particles leaving the ball mill are lifted by a bucket elevator and sent to an air classifier. As the particles from the bucket elevator enters the classifier, they are suspended in an air stream. The air is sucked from the bottom of the classifier and transport the particles into rotating equipment. In this rotational gravity field, large and heavy particles impact the wall and are collected in cyclones as they drop down. Small and fine particles are transported away towards the center of the classifier. The coarse particles are recycled to the mill for further grinding. The fine particles are collected in cement silos and constitute the final cement. Consequently, the overall function of the classifier is to separate coarse particles from fine particles.

2.2 Control Strategy for the Cement Mill Circuit

The objective in controlling the cement mill circuit is to produce cement powder with a desired specific surface area while minimizing the energy consumption (cost) in doing so. The energy consumption is largely connected to rotating the ball mill and its steel balls. It depends only weakly on the cement material loading in the mill. Therefore, the most profitable mode of operation consists of maximizing the production rate while meeting the specific surface area. In this way least energy is used for cement grinding per produced tonnes of cement.

The specific surface area of the material in the product stream is the primary controlled variable in cement mill circuits. In many cement plants, the specific surface area can only be measured by sampling the product stream and analyzing the sample in the lab. In such plants, the specific surface area of the product is only measured infrequently and the result is available to the process control systems with a variable delay of about 30 min (the approximate duration of the laboratory procedure). Modern plants are equipped with an on-line particle size analyzer and the specific surface area is directly available to the process control system. The particle size distribution and thus the specific surface area of the product stream depends on the rotational speed of the classifier, the air speed, the feed rate to the classifier and the particle size distribution of the classifier feed stream. The air speed is often kept constant and the rotational speed of the classifier is manipulated to control the specific surface area of the product stream.

The grinding efficiency in the ball mill depends on its filling. Too little cement material in the mill causes steel balls to hit steel balls without using this energy for crushing material. In addition, the temperature in the mill becomes easily too high in this case. Conversely, as the mill gets loaded with too much cement material, the particles leaving the ball mill are too coarse. They are rejected in the separator and recycled back to the ball mill. The consequence is a very low production rate and too high specific energy consumption. In the extreme case, material builds up in the ball mill such that the diaphragm separating the first and second chambers plugs and material stops flowing. This situation should be avoided. Consequently, one objective in most cement mill circuit control strategies is to control the mass of cement material in the ball mill. The mill should be filled as much as possible without plugging as this leads to the largest production rate. However, the cement mass hold up cannot be measured directly. A so-called pholaphone (microphone) situated outside the cement mill can be used to infer the filling as an empty mill with steel balls hitting steel balls makes more noise than a mill filled with cement material. Although very nonlinearly, the material flowing out of the mill is related to the filling of the mill. This implies that the power used by the bucket elevator is related to the filling of the mill as the power is related to the flow. This elevator power is often used in direct control of the mill filling while the pholaphone is used for override control to avoid plugging.

Consequently, one may control the cement mill circuit by controlling the specific surface area of the cement product stream and the elevator load. This is done by manipulation of the fresh feed flow rate and the rotational speed of the classifier. The main disturbances affecting the cement mill circuit are the hardness of the clinker as well as their size distribution. These disturbances are unmeasurable and affect gains and time constants of the cement mill circuit. They also affect the relationship between the output flow rate and the ball mill cement hold up. This implies that the elevator load set point may be adjusted as consequence of large variations in the hardness.

3. FIR MODEL BASED MPC

In this section we briefly describe the Soft MPC algorithm by Prasath and Jørgensen (2009) used to control the cement mill circuit. The inputs to the MPC are the target values, r, for the process outputs, z, and the measured process outputs, y. The output from the MPC is the manipulated variables, u. The algorithm is based on a Finite Impulse Response (FIR) representation of the model.

3.1 Regulator

Stable processes can be represented by the finite impulse response (FIR) model

$$z_k = b_k + \sum_{i=1}^{n} H_i u_{k-i} \tag{1}$$

in which $\{H_i\}_{i=1}^n$ are the impulse response coefficients (Markov parameters). b_k is a bias term generated by the estimator. b_k accounts for discrepancies between the predicted output and the actual output. In this paper, the output predictions used by the regulator are based on the FIR model (1). Consequently, using the FIR model (1), the regularized ℓ_2 output tracking problem with input and soft output constraints may be formulated as

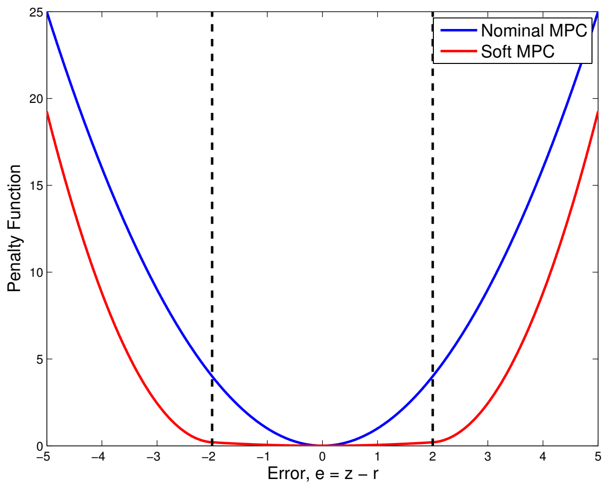

Fig. 4. Penalty function for Soft MPC and Normal MPC.

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

subject to the constraints

$$z_k = b_k + \sum_{i=1}^{n} H_i u_{k-i} \qquad k = 1, \dots N \tag{2b}$$
$$u_{\min} \le u_k \le u_{\max} \qquad k = 0, \dots N-1 \tag{2c}$$
$$\Delta u_{\min} \le \Delta u_k \le \Delta u_{\max} \qquad k = 0, \dots N-1 \tag{2d}$$
$$z_k \le z_{\max,k} + \eta_k \qquad k = 1, \dots N \tag{2e}$$
$$z_k \ge z_{\min,k} - \eta_k \qquad k = 1, \dots N \tag{2f}$$
$$\eta_k \ge 0 \qquad k = 1, \dots N \tag{2g}$$

in which $\Delta u_k = u_k - u_{k-1}$. (2) can be converted to a dense convex quadratic program and solved efficiently (Prasath and Jørgensen, 2008, 2009).

In a model predictive controller only the first vector, u_0^*, of $U^* = \left[(u_0^*)' \ (u_1^*)' \ \dots \ (u_{N-1}^*)'\right]'$, is implemented on the process. At the next sample time the open-loop optimization is repeated using new information coming from the latest measurement.

Figure 4 illustrates the stage cost function for ℓ_2 model predictive control (nominal MPC) and ℓ_2 model predictive control with a dead zone (soft MPC). The stage cost function, or penalty function, is plotted as function of the set-point error, $e = z - r$. The penalty function of the nominal MPC is a quadratic function. 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 growths 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. By having the penalty small within the soft constraints, the controller does not react much to small errors. In this way we avoid that the controller introduces significant real disturbances to the process because it reacts to, say, measurement noise or plant-model mismatch. Outside the soft limits, it is assumed that the deviation from target is due to a real process disturbance, and the soft MPC may be designed to react in the same way as the nominal MPC.

3.2 Simple Estimator

To have offset free steady state control when unknown step responses occur, we must have integrators in the feedback loop. This may be achieved using a FIR model in difference variables. Assume that the relation between the inputs and outputs may be represented as

$$\Delta y_k = \Delta z_k = e_k + \sum_{i=1}^{n} H_i \Delta u_{k-i} \tag{3}$$

in which Δ is the backward difference operator, i.e. $\Delta y_k = y_k - y_{k-1}$, $\Delta z_k = z_k - z_{k-1}$, and $\Delta u_k = u_k - u_{k-1}$. This representation is identical with the FIR model (1)

$$y_k = z_k = \hat{b}_k + \sum_{i=1}^{n} H_i u_{k-i} \tag{4}$$

if $\hat{b}_k$ is computed by

$$e_k = \Delta y_k - \sum_{i=1}^{n} H_i \Delta u_{k-i} \tag{5a}$$

$$\hat{b}_k = \hat{b}_{k-1} + e_k \tag{5b}$$

Note that in the regulator optimization problem $b_1 = b_2 = \ldots = b_N = \hat{b}_k$ at each time instant. This is based on the assumption that the disturbances enter the process as constant output disturbances. Of course this may not be how the disturbances enter the process in practice, and significant performance deterioration may result as a consequence of this representation.

4. CLOSED-LOOP SIMULATION

The cement mill circuit is simulated using a rigorous simulator, ECS/CEMulator (FLSmidth Automation, 2009). ECS/CEMulator is based on a nonlinear distributed model and is normally used for operator training. In this paper we use it as a realistic surrogate for a real cement mill circuit to test our controllers.

We consider 2×2 MPC controllers based on the models $Y(s) = G(s)U(s)$ with $Y(s) =$ [Elevator Load; Fineness] and $U(s) =$ [Feed; Separator Speed]. Doing step response experiments on the simulated cement mill circuit, we identify a transfer function for the nominal situation

$$G(s) = \begin{bmatrix} \dfrac{0.62}{(45s+1)(8s+1)} e^{-5s} & \dfrac{0.29(8s+1)}{(2s+1)(38s+1)} e^{-1.5s} \\ \dfrac{(-15)}{(60s+1)} e^{-5s} & \dfrac{5}{(14s+1)(s+1)} e^{-0.1s} \end{bmatrix}$$

This model is used by the model predictive controllers. In the case when the hardness of the clinker is perturbed and deviate from the nominal situation, the real transfer function is unknown to the controller and is approximately the above transfer function with a modified gain matrix, $K = [0.2\ 0.12;\ -8.0\ 2.0]$.

A normal MPC with an ℓ_2 penalty function and a Soft MPC using an ℓ_2 penalty function with an almost zero dead zone as illustrated in Fig. 4 are designed. Using ECS/CEMulator from a steady state, a significant change in hardness of the material is introduced at time 1.35 hr and the controllers are switched on at time 2.0 hr. The resulting closed loop profiles for the Normal MPC and Soft MPC are illustrated in Fig. 5. It is evident by the simulations that the variation of the output variables are more or less comparable for the two MPCs, but the Soft MPC manipulates the MVs in a more plant friendly manner than the Normal MPC. Consequently, most practitioners would prefer the Soft MPC to the Normal MPC as it gives rise to less plant wear.

5. CONCLUSION

In this work we have provided a control strategy for a cement mill circuit. By simulation with a rigorous process simulator, we have demonstrated how the Soft MPC may be used to implement this control strategy despite the significant plant-model mismatch unavoidable for cement mill circuits. In particular, the Soft MPC provides more plant friendly control than Normal MPC.

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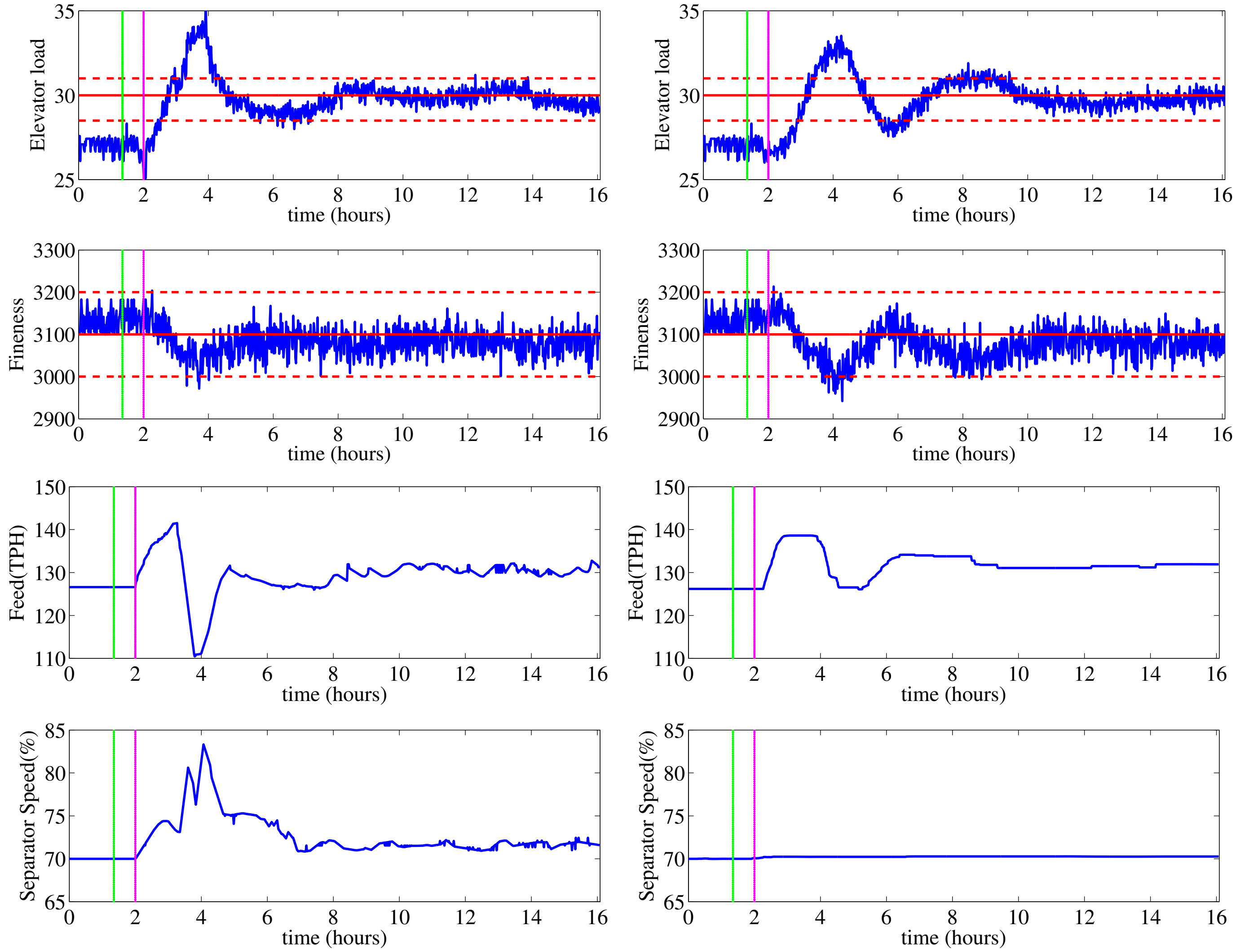

Fig. 5. Normal MPC (left) and Soft MPC (right) applied to a rigorous nonlinear cement mill simulator, ECS/CEMulator. The disturbances (change in hardness of the cement clinker) are introduced at time 1.35 hour (green line) and the controllers are switched on at time 2 hour (purple line). The soft constraints are indicated by the dashed lines.

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