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PROCESS CONTROL FOR CEMENT GRINDING IN VERTICAL ROLLER MILL (VRM) A REVIEW

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ABSTRACT

The power ingesting of a grinding process is 50-60% in the cement production power consumption. The Vertical Roller Mill (VRM) reduces the power consumption for cement grinding approximately 30-40% associated with other grinding mills. The process variables in cement grinding process using VRM are strongly nonlinear and having large time delay characteristics also dynamics changes within 2-4 minutes. The fast dynamics necessitate closer attention to the process condition and taking corrective action in time. In this paper, the various conventional and modern control strategies to control the process variable available in VRM are discussed.

Keywords: vertical roller mill, model predictive control, proportional integral and derivative control, artificial neural networks, fuzzy logic.

1. INTRODUCTION

The VRM is a type of grinding mill integrated with multi functions such as grinding, drying and separation, used for grinding of coal, petroleum coke and minerals. Most recently this technology has been employed for comminution of Blended, Slag and Port Land cement grinding**.** The cement grinding and drying system be dovetail of a large array of obsolete incompetent equipment and was completely replaced by a single VRM, it improves the fineness and diminish the maintenance and power consumption [1, 34, 36]. Optimization of cement grinding using standard bond grinding calculations based on population balance models is successfully applied [4, 38]. Various grinding laws, energy relationships, control factors and controller design for cement grinding are discussed in [37].

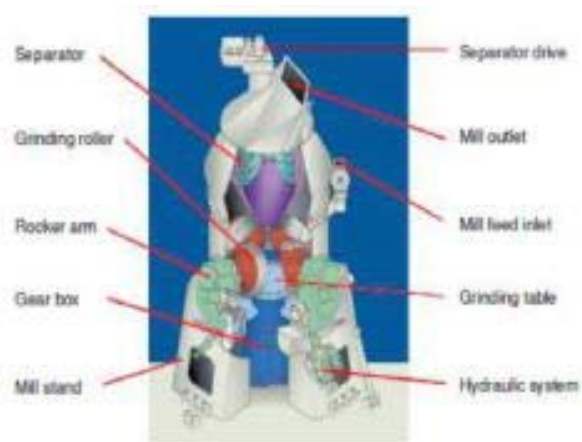

Figure-1. Vertical roller mill for cement grinding [13].

VRM shown in Figure-1 uses hydraulically hard-pressed conical shape 2-4 rollers against the horizontal revolving grinding table. To enhance comminution, the axes of table and rollers do not traverse in the plane of the table and approximately 15^0 inclination angles between roller axis and table, the relative motion appertain both sliding and rolling. Mixed raw materials are fed using the feeding belt conveyer through feeding mouth along with feed pipe. With the help of louver ring, a rising air current at the periphery is directed; while the rollers are rotating, material is heading onto the center of the table and thrown outward by rotation beneath the rollers. Coarse material fall onto the feed table, fines pass out with the air current and the air sweep passes all the way through an integral rotating classifier. After the last feed input the central to the mill table, due to mill and roller's relative movement, materials get into the grinding layer between the roller and the mill. In suspension between classifier and table, material drying transpires will takes place. The unstable grinding bed causes the VRM to vibrate. Water is directly sprayed into the bed to make dry mill feed, which is usually alleviate and cause of material instability. The success or failure of the VRM production depends on pressure difference between inlet and outlet, the grain size of the raw material [1, 2].

For VRM the production capacity denotes both the capacity of grinding and drying of mill. The grindability affects the capacity of grinding, type of mill and roller pressure. The capacity of the mill is calculated Using $G=K * D$ 2.51

Where, G is capacity of the mill, *K1* is roller mill coefficient and D is table diameter.

2. PROCESS CONTROL OF VRM

The conventional control system of VRM composed of field staff to adjust the few process parameters manually with their experience, it leads the system unstable, high power consumption and low productivity. For stable long term operation, when the system establishes large fluctuations regulate the grinding dust collecting fan speed and when the system under small fluctuations adjust machine speed [2]. The various parameters used for process control in VRM are given in Table-1.

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Table-1. Various VRM parameters used for process control [34, 36].

Process measured variables	Manipulated variables	Disturbance variables
Fineness (Blaine) or residue	Grinding stock feed	Material grindability
Mill motor speed	Classifier speed	Material temperature
Mill air flow	Mill fan speed	Material moisture
Mill differential pressure	Water injection	Mixture composition
Product transport volume	Grinding aid injection	Composition of raw material
Temperature after the mill	Hot gas	Grinding roller wear
Mill vibrations	Fresh air	

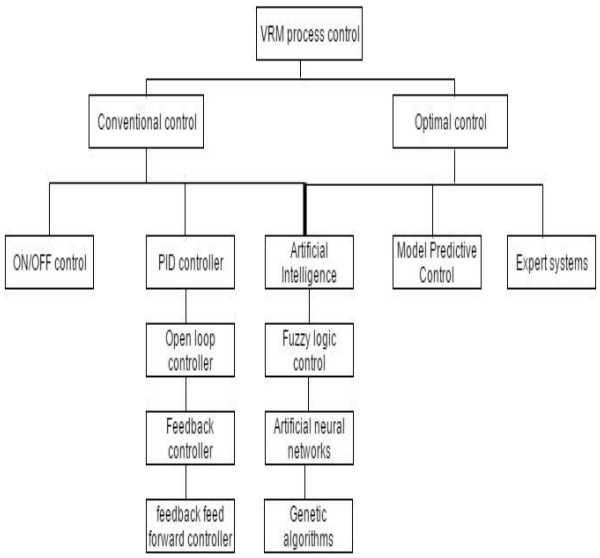

Figure-2. VRM control classification [42].

2.1 Classical control

Controlling single input single output (SISO) systems using conventional methods are based on Laplace transformation theory. In SISO only one measured variable is available for feedback out of many variables and therefore classical control methods are more accurate for linear, time-invariant SISO systems.

2.2 PID, neural, fuzzy and hybrid controllers

In the presence of modest nonlinearities the Proportional Integral and Derivative (PID) controllers are comparatively uncomplicated to robust and tune because the plant parameters are frequently uncertain and difficult to estimate. For complex nonlinear systems online tuning is used to extremize the cost function to provide optimized control. Ziegler Nichols and Cohen Coon methods are popularly used for PID tuning. With less complexity in control PID control is considered as consistent approach but parameterization of the coefficients follows no general rule [5].

Table-2. Effect of increasing parameter values of PID controller independently on the response [7, 44].

Parameter	Settling time	Steady state error	Speed of response	Rise time	Overshoot	Stability	Accuracy
Proportional gain Kp	Tiny change	Decrease	Increases	Decrease	Increase	Deteriorate	Improves
Integral gain KI	Increase	Decrease significantly	Decreases	Decrease	Increase	Deteriorate	Improves
Differential gain KD	Small Decrease	No effect	Increases	Small Decrease	Small Decrease	Improves	No impact

Table-3. Comparison of PID tuning methods [42, 44].

Tuning method	Remarks
Manual (Online)	Tuning with experienced personals without mathematics
Ziegler- Nichols (Online)	Uses trial and error method, process upset is present
Cohen-Coon (Offline)	Some mathematics required, good process model required
Software tools(Online or offline)	Uses non steady state tuning with training

The foremost disadvantages of Neural Networks (NN) are the weighty computational intricacy and slow convergence speed. To conquer these wavelet functions are used in the hidden layer of NN network structure as a substitute for the threshold function otherwise NN control is not suitable for local minimum of the error surface. Manufacturing tolerances causes' invertible parameter variations are effectively considered using the self-tuning algorithms by adjusting process set points. To overcome deterministic type of uncertainties and random instant disturbances, feedback controller like fuzzy sliding mode control is discussed in [25]. For better performance of the recurrent wavelet NN by reducing the computational difficulty Modular Recurrent NN by means of pipelined architecture was discussed in [6].

To recover the regulating performance of a nonlinear plant a fuzzy feedback controller with adaptive feed forward control scheme is discussed in [33]. The output harmonic component error is cancelled with the large harmonic terms present in the system, but by using natural frequency selection the harmonic terms are restricted. The overall performance of the fuzzy logic controller is still in testing as because of its empirical methodology.

Fuzzy control has the poor unwilling interference ability and with the integration of PID effectively improves the control performance but this controller method is not reliable and faster. Neuro-fuzzy controller needs accurate mathematical model for better performance. The design of sliding model restricts the application of fuzzy sliding mode control for nonlinear plants using fuzzy control theory.

2.3 Modern control

The multiple input and multiple output (MIMO) system is controlled using modern control theory is mainly based on state variable representation with set of first order differential equations. Designing a highly nonlinear plant is fairly challenging task using classical control approaches because they concentrate on reminiscent of the plant at different operating points uses local models. Approximation is used in nonlinear state dependent constraints to make computationally simpler optimization problem in nonlinear plants.

2.3.1 Model predictive control (MPC)

MPC algorithms are accepted because they address state and control constraints much precisely. To reproduce the transient and steady state responses MPC uses dynamic model, at each decision time point it uses first - principle equations to calculate the optimal future control law over a finite predictive horizon and related sequences starts from the present state. MPC uses recursive type overall optimization process at succeeding decision points by means of first control input to solve the performance measure. The new present state is updated from the feedback information by calculating the new control and state sequences. The variation between the measured and predicted outputs are considered by maintaining the important variables close to the tracking point and maintaining all the measured variables inside the limits and extremize the control exertion with constraints in manipulated variables and the feedback from measurements is integrated [23]. The performance index being selected is different for various problems and influences the performance of the plant. For dynamic systems multi objective modeling, optimization and control is necessary as the system requirements are more conflict.

Full operating range is separated into many local operating points to effectively control the nonlinearity present in the systems and using prediction error identification method a local linear model is designed offline. A norm bounded model uncertainties present in the input saturated uncertain discrete time linear systems are absolute to allow the online updating of terminal cost function at each time instant a robust predictive control scheme is preferred. Optimization problems associated to embedding schemes are typically convex and efficiently solvable also in cases with hundreds of variables. On the opposite, direct methods lead usually to nonlinear non-convex optimization [15].

Linear Model Predictive Control (LMPC) capitulate satisfactory performance for linear systems only when the process operates close to nominal operating points and for wide operating ranges the nonlinear control strategy futile. For strong nonlinear plants, MPC gives satisfactory control by using nonlinear dynamic model for prediction. In Nonlinear MPC (NMPC) the selection of nonlinear model plays vital role. Field Programmable Graphical Array and ASIC's are successfully applied to solve the cost function and to find the optimum control law for real time applications. Quadratic programming is extensively used to solve the optimization problems using ASIC recently for complex nonlinear plants and same is adopted successfully in NMPC [15, 16].

Multivariable character in MIMO systems causes high interaction and nonlinearity between process variables [29]. In Decentralized MPC average preparation time for controller design is less with less number of modelling errors. For dynamical coupling systems; without any compensation methods produces stable response without overshoots, but undershoot present with more settling time and it limits the existence of decentralized MPC for interconnected interacting systems. Centralized MPC produces lengthiest settling time; displays undershoot with less average preparation time. Sub models available in interacting MIMO systems shares the common inputs and states causes' practical exist of centralized MPC to reduce the modeling errors [3, 9, 10].

To achieve efficient approximation adaptive controllers uses data driven approaches and online parameter estimation. Data driven model using regression matrix to control nonlinear plants by using either offline or online data with uncertainties in parametric and dynamics is discussed in [20]. The dynamic uncertainties are difficult to measurement and construct in dynamic systems and therefore approximation is needed to design an effective controller. The adaptive controllers track the reference signal with a small neighborhood of zero, as it

uses the existing state of the plant. The large preparation data set collected past related to real time plants may not suits for adaptive controller design and also time consuming one for calculations of control law. Parameter uncertainties and un-modeled dynamics causes un-stability and dynamic in-balances in the system are overcome using adaptive control with the integration of data driven and model predictive control methods. Output uncertainties causes speed fluctuations in dynamical systems are conquered using feed forward controller with feed forward compensation and the integration of other advanced control structures. For the control of complex dynamic processes, Neuro adaptive controllers provide good performance with less settling time and overshoot [25]. Lyapunov direct method defines the asymptotically convergence condition of the nonlinear adaptive control system. Nonlinear transformation methods require exact knowledge of the nonlinear process model even the process parameters are not known. Stability convergence methods are more complicated to apply for the real time systems because of either partially or frequently unknown mathematical equations or their forms [33].

The increased complexity and not guaranteed optimality makes the adaptive control infeasible for complex nonlinear processes. The overall system performance depends on the controller and observer design in modern control theories. The sliding mode control provides good results for robustness issue it is limited as because it depends on other control approaches. Table-4 represents various problems in VRM and necessary actions to overcome those problems. In Table-5 the various technologies used in cement industry. Table-6 represents various controllers and their merits and demerits.

Table-4. Possible problems in VRM process control and necessary actions to be taken for proper control [1, 2, 30, 32].

Type of problem	Reason for problem / Solution to reduce the effect of the problem
Feed bins almost empty	Stop the mill and fill with feed
Oil pressure or oil flow through mill gear minimum	Check leakage in piping, cooling water supply, oil pump, oil levels, oil temperature
Grinding pressure decreases	Check hydraulic system piping is leaking, oil level in tank for hydraulics minimum, oil temperature in hydraulics minimum and malfunctioning of valves, oil pump fault
Mill vibrations too high	If differential pressure is high reduce feed supply, increase feed supply else check water injection and lift rollers at excessive vibrations
Feeder units disturbed	Increase feed supply from other feeders and stop the mill if feed transport fails
Heat generator is failing	Check the oil gas filter, ignition gas bottle, adjust ignition and main burners and pre heating of oil
Mill fan bearing temperature maximum	Stop fan and mill, check supply of cooling water, greasing of fan bearings
Mill outlet temperature too high	Check the hot air amount, hot gas temperature, open cold air damper adjust or close hot gas damper, decrease oil for heat generator and increase water injection
Oil pressure or oil flow through the separator gear minimum	Check leakage in piping, oil pump fault, oil level minimum, oil temperature and cooling water supply
Starting the mill without grinding layer	Fill mill with material before start, by starting transport devices in correct sequence and fill in 300-500kg of material
Mill outlet temperature too low	Increase raw material moisture, hot air amount, oil for heat generator, close cold air damper, adjust or open hot gas damper, adjust or open mill fan damper, decrease water injection
Mill output too low	Check grinding pressure, differential pressure, grindability of raw material changes, coarser raw materials, raw materials too wet and table and roller segments are worm, product fineness very fine,
Mill product too coarse	Increase speed of separator and feed supply
Mill product too fine	Increase feed supply and decrease speed of separator rotor

Table-5. Status of technology used in cement grinding (National council for cement and materials).

	Global technology plants	Modern plants	Low technology plants
Plant size (TPD)	6000-12000	3000-6000	300-1800
Process control	DDC/ Nero fuzzy expert systems/ MPC	DDC/Fuzzy logic expert systems	Hard wire/ PLC/ Relay logic
Grinding	VRM, roller press with dynamic classifier	VRM, roller press with dynamic classifier	Ball mill with or without traditional classifier
Energy consumption	70-80 kwh/t, cement 675-740 kcal/kg cl	75-85 kwh/t, cement 700-800 kcal/kg cl	90-100 kwh/t, cement 900-1000 kcal/kg cl

Table-6. Various controllers and their merits and demerits [3, 7, 9].

Type of Controller	Merits	Demerits
ON/OFF	Used when precise control is not necessary, useful in slow changing systems	Considerable over shoots and undershoots, poor performance when controlling rapid system fluctuations, not suitable for chemical processes
PID	Best suits for under damped process, processes with slow dynamics, systems having not very large time delays and second and higher order systems	Not suits for dynamical processes, nonlinear processes, Process with uncertainties, disturbance processes, for constrained in the context of controlling resonant, unstable or integrating processes
Neural Network	Approximates any function regardless of its linearity, great for complex/abstract problems	Requires a shit load of training and cases
Fuzzy Logic	Intuitive knowledge based design, validation, consistency, redundancy and completeness is checked in rule base, best suited for process with modeling difficulties, unknown plants, process with lot of adjustable parameters	Time consuming, performance robustness tradeoffs in not Usually taken into account in tuning
Feed forward	No sensors needed to measure the control variables and suitable only for the systems whose input and disturbance are predictable	It is not a generalized controller, works only for particular systems also less accurate for dynamic systems
Feedback	Process characteristics are independent of operating conditions, signal distortion due to non-linear characteristics of the components is greatly reduced, high performance in the presence of uncertainty	Instabilities present due to delay present in feedback, trade-offs present between stability and performance of the system, creates oscillatory response with reduced overall gain of the system
Adaptive control	Nonlinear behavior as in case of complex chemical or biochemical reaction, appreciable dead time, when control system for new process is commissioned	No real learning or intelligence, estimation over a continuum is challenging task
Model Predictive	Increased throughput, minimizing the operating cost while meeting constraints, superior for processes with large number of manipulated and controlled variables, allow time delays, inherent nonlinearities	Requires accurate dynamical model and good knowledge about the process, the development price and preparation time to design controller is more
Decentralized MPC	Average preparation time for controller design is less with less number of modelling errors for dynamical coupling systems, without any compensation methods produces response without overshoots	Undershoot present with more settling time
Centralized MPC	Faster settling time without overshoot, provides stable response	Systems with many interacting subsystems are difficult to control, MIMO type system optimization is time consuming and average preparation time is more.

3. CONCLUSIONS

The VRM for cement grinding system consists of many interacting and dynamic coupling sub systems. The settling time is large and sub systems are highly nonlinear. The conventional PID controller provides better performance results only by approximating the plant to

linear and controls the loops individually. PID is not best suited for nonlinear dynamical process without linear approximation. Neuro- Fuzzy systems gives comparatively good performance with PID, but these methods are not reliable and fast for industrial applications. The adaptive control is complex to design for MIMO and optimality is not guaranteed. Linear MPC gives good results for linear plants but for nonlinear processes approximation is needed. For highly nonlinear systems like VRM, with many interacting sub systems, decentralized MPC gives better performance with minute undershoot.

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