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Online monitoring and control of particle size in the grinding process using least square support vector regression and resilient back propagation neural network

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ABSTRACT

Particle size soft sensing in cement mills will be largely helpful in maintaining desired cement fineness or Blaine. Despite the growing use of vertical roller mills (VRM) for clinker grinding, very few research work is available on VRM modeling. This article reports the design of three types of feed forward neural network models and least square support vector regression (LS-SVR) model of a VRM for online monitoring of cement fineness based on mill data collected from a cement plant. In the data pre-processing step, a comparative study of the various outlier detection algorithms has been performed. Subsequently, for model development, the advantage of algorithm based data splitting over random selection is presented. The training data set obtained by use of Kennard–Stone maximal intra distance criterion (CADEX algorithm) was used for development of LS-SVR, back propagation neural network, radial basis function neural network and generalized regression neural network models. Simulation results show that resilient back propagation model performs better than RBF network, regression network and LS-SVR model. Model implementation has been done in SIMULINK platform showing the online detection of abnormal data and real time estimation of cement Blaine from the knowledge of the input variables. Finally, closed loop study shows how the model can be effectively utilized for maintaining cement fineness at desired value.

1. Introduction

Online sensors continuously measure the different process variables and hence play the most important role in continuous process monitoring and control. However, there are fewer reliable and accurate hardware sensors available for accurate online measurement of product quality. Soft sensors perform online estimation of variables (mostly related to product quality) which are otherwise difficult or impossible to monitor online, using easily measurable variables. Continuous online monitoring of product quality will result in increased productivity and reduction in energy loss, undesirable by-product formation and safety hazards [1,2]. Data-driven soft sensors are becoming increasingly popular in the process industries because of the various difficulties associated with developing first principle models such as poor process understanding, model complexity and/or difficult to determine model parameters [3,4]. Successful application of soft sensors for product quality estimation has been reported in various industries such as petroleum refining and petrochemicals [5–7], polymer [8,9], steel [2,10,11], bioprocesses [1,12,13], rotary cement kiln [3,14], pulp and paper [15] and thermal power plant [16,17].

Online measurement of particle size is important for proper quality maintenance and efficient control of a grinding process. However hardly any reliable physical sensors are available for continuous online measurement of particle size. Even if real sensors are available for online particle size monitoring, such sensors require frequent cleaning and maintenance because of continuous exposure to fine particles [18]. The research works reported in the literature for particle size soft sensing have used back propagation neural network [19,20], non-linear ARX [18,21], extended Kalman filter [22] and radial basis function neural network [23,24]. The NARX and Kalman filter models reported in the literature assume the availability of a real sensor and can only be applied in case of temporary unavailability of the physical sensor. Unfortunately, in many comminution processes, no such sensors are available.

Grinding operations in cement industries especially that of raw material and clinker account for approximately 75% of the total production cost [25]. In the cement manufacturing process, the particle size is expressed as cement fineness or cement Blaine

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Notations

c_i	Centre associated with ith RBF neuron
D_i^2	Euclidean distance between two input vectors
I_j	Net input to jth pattern neuron in a regression neural network
K	Kernel function for LS-SVR model
L	Quadratic loss function for LS-SVR model
$Q_{0.25}$	First quartile of a data set
$Q_{0.75}$	Third quartile of a data set
x_i	ith value in an input vector
$\bar{x}$	Mean value of a data set
$x_{0.5}$	Median of an input vector
$x_{\max}$	Maximum value of an input vector
$x_{\min}$	Minimum value of an input vector
b	Bias value for LS-SVR model
ξ	Slack variable for LS-SVR model
γ	Skewness of a data set
α	Lagrange multiplier for LS-SVR model
κ	Kurtosis of a data set
$\phi(x)$	RBF network basis function; non-linear transformation function of LS-SVR
σ	Standard deviation of a data set, Scaling parameter of RBF network, spread parameter of regression network
var	Variance of a data set
w	Weight vector in feature space of LS-SVR model
w_i	hidden to output layer weight associated with ith RBF neuron
$\bar{y}$	Mean value of actual outputs
$\hat{y}$	Model predicted value
$\bar{\hat{y}}$	Mean value of the model predicted outputs
BPNN	Back propagation neural network
GDM	Gradient descent with momentum algorithm
GRNN	Generalized regression neural network
K–S	Kennard–Stone
LM	Levenberg–Marquardt algorithm
LS-SVR	Least square support vector regression
MAE	Mean absolute error
MAPE	Mean absolute percentage error
NSE	Nash–Sutcliffe efficiency
RBFNN	Radial basis function neural network
RP	Resilient back propagation algorithm
RMSE	Root mean square error
TIC	Theil's inequality coefficient
VAF	Variance account for
VRM	Vertical roller mill

which is surface area per unit mass. A higher Blaine indicates higher fineness and vice versa. Lower than prescribed cement fineness indicates poor quality of the finished product resulting in more recycling and thereby increases the grinding cost further. After grinding, the cement is separated from the carrier gas (hot air) in the bag house. Therefore, very fine cement particles will lead to loss of cement. This loss happens due to two reasons. Ultrafine cement particles will escape out along with the carrier gas in the bag house inside the plant. Subsequently, after bagging, continuous leakage of fines from cement bags takes place during handling and transportation. The aforementioned facts highlight the need for production of cement with proper fineness. At present, the fineness is measured by offline laboratory sampling. Since no hardware sensor is available for online monitoring of cement Blaine in the grinding process, a soft sensor based on the input parameters of the comminution process will largely help the plant operators to adjust the process inputs so as to produce cement with desired fineness. The product particle size in a cement mill is a non-linear function of the mill inputs [26] and because of this non-linearity, accurate mathematical modeling of the cement grinding process is highly difficult. Therefore, data based approach has been adopted in this work for grinding process modeling.

The study of existing literature on modeling of grinding processes has led to identification of the following gaps which the authors have tried to address in this work. First, despite the reasons cited above on the importance of maintaining proper fineness of cement, there has been little effort for soft sensing of cement fineness. Second, most of the particle size soft sensing works have focused on ball mill based grinding process. However, at present there is a gradual shift from use of ball mill to use of vertical roller mill (VRM) for clinker grinding. This change, from largely used ball mills towards vertical roller mills is mainly due to certain advantages offered by VRMs over ball mills such as: drying, grinding and classification operations carried out in a single equipment, lower energy consumption and compact layout. Modeling of a vertical roller mill is different from that of a ball mill in the sense that variables considered for model development are different in these two different grinding processes. Moreover, VRMs have very fast dynamics as compared to ball mills. However, to the best knowledge of the authors, very few research has been done in the area of vertical roller mill modeling for estimation of product particle size. Further, the non-linear modeling using the principle of support vector regression has not yet been applied to grinding processes and even though neural network models have been developed, a comparison of the performances of different types of neural network models has not yet been reported for grinding processes.

Recently, VRM modeling for real time monitoring of cement fineness using standard support vector regression and fuzzy inference techniques has been reported by the authors [27]. This article reports the performance of three types of feed forward neural networks and least square support vector regression (LS-SVR) models as soft sensors for online monitoring of cement fineness. The models are developed from actual process input–output data taken from a cement plant having a clinker grinding capacity of 235 t/h. The raw data collected from plant history were processed for outlier removal. The processed data were then split equally into training set and validation set using Kennard–Stone maximal intra distance criterion. The training data were used to develop LS-SVR model and different neural network models: back propagation neural network (BPNN) model, radial basis function neural network (RBFNN) model, and generalized regression neural network (GRNN) model. Performances of the different models were compared by simulating the validation data and determining six different model performance indices: Mean absolute error (MAE), Root Mean Squared Error (RMSE), correlation coefficient, variance account for (VAF), Nash–Sutcliffe efficiency (NSE) and Thiel's inequality coefficient (TIC). Simulation results show that the model developed using resilient back propagation algorithm performs better than RBFNN, GRNN and LS-SVR models. The best performing BPNN model has been implemented in SIMULINK platform, showing the real time estimation of cement Blaine from the knowledge of the input variables. Finally, the model has been used in a closed loop, illustrating how the predictive capability of the developed model can be utilized for controlling the cement fineness within the desired value in the presence of changes in input conditions.

The significant works reported in this article are as follows: First, in the data based modeling for engineering processes, the splitting of the available data for model development is mostly done by random