

Soft Sensor for Online Cement Fineness Predicting in Ball Mills

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ABSTRACT

The cement fineness is a determining factor in product quality. Estimating this variable in real-time can be extremely useful to maintain the desired characteristics of the product during the cement grinding process, which will also allow a significant increase in the system energy efficiency. This paper describes the design and implementation of a soft sensor based on a backpropagation neural network model to predict the cement fineness online in a ball mill. The input variables of these models were selected by studying the cement grinding process, applying Spearman's rank correlation, and the mutual information (MI) algorithm. The fineness results of laboratory tests were collected to obtain the output variable and for training the models. The procedure of extracting, analyzing, treating, and cleaning raw data received from the factory and the intensified hyperparameter adjustment of the predicting model provided excellent soft sensor performance. The developed system was tested in a cement grinding process and demonstrated the ability to provide information about the variables previously obtained only through offline laboratory tests.

Keywords: Cement fineness, artificial neural network, ball mill, product quality.

1. INTRODUCTION

Cement is a powder material, forming a paste with water, that hardens due to hydration reactions, creating strength and durability. The cement fineness is monitored and controlled during the grinding process to obtain the desired compressive strength. The smaller the particle size, the larger the surface for the reaction between the cement and water and, consequently, the greater the compressive strength obtained.

Typically, aiming to know the fineness, cement plants collect a representative sample of the material for laboratory tests during the cement grinding process. This analysis consists of passing the collected material through a sieve to analyze the material retained [1]. This procedure is performed once every two hours and can be done every four or eight hours in industries with many mills. In situations that significant changes in the separator rotor speed are necessary to correct the fineness, this long interval among analysis becomes detrimental to the process performance because it affects its energy consumption and causes instabilities [2]. The separator is equipment that separates the cement fine enough for the final product from the material that must return to the mill to reduce the particle size. However, reduce the particle size means higher energy

consumption to produce one ton of cement. This relationship is an exponential function with 1.6 power [3]. The cement grinding is responsible for approximately 40% of the energy consumed in a cement plant, considering an average of 110 kWh for the production of one ton of cement [4,5]. Thus, a model capable of predicting the cement fineness in real-time can improve the two indicators of the cement grinding circuit performance: energy consumption and product quality.

Although physical sensors for online estimation of cement fineness are available on the market, they are expensive and, due to their exposition to fine particles from the ball mill, they require constant cleaning and maintenance [6].

In recent years, some studies have been conducted to develop models capable of estimating the cement particle size for the ball and vertical mills [7]–[9]. These works are of great importance for the cement industry because they provide real-time information on variables that previously were only obtained by laboratory analysis. They introduce the development of a soft sensor using artificial neural network models to solve the industrial problem presented. Soft sensors are systems that have a model internally implemented and provide an opportunity to improve the performance of a process [10]. These models avoid problems such as measurement errors and delays, lack of availability or reliability of physical sensors, distance from the measurement point, high cost, and several other factors.

Most soft sensors are based on black-box models and require delicate and time-consuming setups to predict the interest parameters. However, if there is already a reasonable amount of historical data collected, even for a complex system such as the cement grinding process, the development of a soft sensor using a black-box model becomes feasible.

1.1. Our Contribution

This paper presents the design and development of a soft sensor to predict the cement fineness in real-time. The data corresponding to the input variables were obtained from the measurable variables of the cement grinding circuit during the regular and real production of an industrial process, herein referenced as *process 1*.

The first and most essential step in developing the soft sensor is the extraction of raw data from the plant and its preprocessing. In this stage, cleaning, rationalization, and complementing the records are performed. This process allows developing high-quality data, and as a consequence, it improves the performance of the model [10]. In contrast to the relevant works cited to estimate fineness in real-time, this paper focuses on the treatment of raw data received from the plant through the application of statistical concepts, as well as a technique based on the isolation of anomalies for outlier analysis.

The selection of model input variables is another essential step. Only those that contain more information about the cement fineness shall be used as input variables for the development of the black-box model. Thus, the variables were selected using three main stages. First, the collaboration between researchers and the cement plant to study and analyze the grinding system. The second stage involves the use of Spearman's rank correlation coefficient [11]. Finally, from the subset of input variables selected by this technique, the application of mutual information (MI), proposed by Kraskov et al. [12], was used.

This work exposes soft sensor implementations for two subsets of input variables. The soft sensors developed, one for each subset achieved, have black-box models based on a multi-layer perceptron neural network (MLP) implemented. The results of laboratory fineness tests were used for training the models, which were able to provide online fineness estimation every minute. This system was effectively tested in *process 1*.

1.2. Paper Structure

Section 2 of this paper provides a simplified description of the cement grinding circuit. Section 3 presents the procedures and methods used for data collection and preprocessing. Section 4 shows the steps taken to select the subsets of input variables. Section 5 describes the proposed model structure, while Section 6 exposes and analyzes the

achieved experimental results. Finally, Section 7 presents the conclusions of this work.

2. CEMENT GRINDING CIRCUIT

The first step in the cement grinding process is to load the hoppers with materials according to the cement composition. Scales or load cells are installed under each hopper to control the correct amount of each material. Usually, the hopper material is ground in a ball mill. Figure 1 shows a simplified scheme of this process.

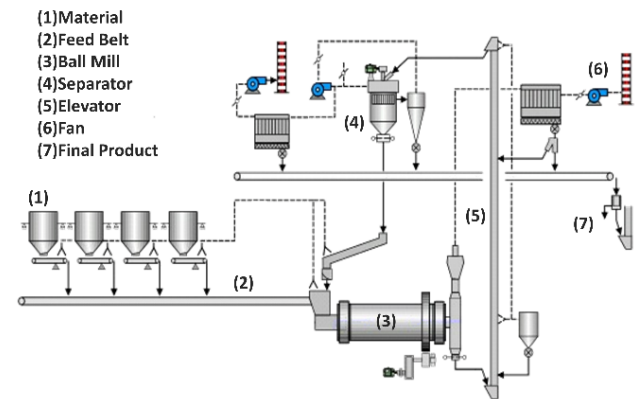


Figure 1 Simplified scheme of the cement grinding circuit

Generally, traditional ball mills are divided into two chambers and use vibration or noise sensors to measure the fill levels of these. Besides, there is the monitoring of the current and power of the mill main motor, since these parameters also indicate the mill fill level.

As the mill rotates, the movement of the balls grinds the material. An exhaust fan located at the mill outlet controls an air sweep that helps to drag the sufficiently fine particles. Inside the mill, the material passes through the diaphragm and reaches the second chamber, where it will continue to be ground, providing a further reduction in the particle size. The appropriate sensor measures the material temperature at the mill outlet. When the ground material reaches the mill outlet grid, its lifter blades take the cement to the elevator, which transports it to the separator. The material from the elevator is released into an airstream inside the separator. The separator rotor provides a centrifugal force to separate coarse from fine particles. If the particle is coarse, it will be repelled and sent to the mill input until it is fine sufficient to pass through the separator, to posteriorly, to compound the final product.

3. DATA COLLECTION AND PREPROCESSING

The sampling procedure is carried out by the area operators who collect cement on time at the final product stage and

take it to the laboratory for analysis, every 3 hours, on average. These laboratory analyses usually take 1 hour to be ready, counting the sampling time.

After the conclusion of the laboratory tests, the operators store the analyzed data and the sampling date and time to correlate with other process variables in a structured database, using a web platform interface. Data were collected for 6 months.

Mejić et al. [9] present the development of a new algorithm to extract the delay times corresponding to each input variable correlated with the cement fineness. On the other hand, Stanišić et al. [8] discuss the introduction of the delay times in input variables base on experience and knowledge about the process in collaboration with plant specialists. Unlike the process presented in this paper, both works use automatic samplers and collect several samples before performing laboratory analysis. In this sense, it is feasible to use the introduction of delay times in the input variables based on the approach proposed by Stanišić et al. [8]. First, the knowledge in the process is fundamental for soft sensor development, and second, they achieve good results in their work.

Considering normal conditions, when the mill starts to rotate, there is always material in the circuit of the last operation. Tests carried out by the factory showed that the delay between the start of the grinding process and the detection of rejects at the separator outlet is 7 minutes. Therefore, it needs to introduce a delay on variables related to the mill input. Table 1 shows the introduced delay time for each input variable.

The data obtained refer to the production of two different cement types. *Cement type 1* must have a fineness of 8% and a standard deviation of $\pm 2\%$, and *cement type 2* must have a fineness of 1.5% and a standard deviation of $\pm 0.5\%$. After completing the data collection, the preprocessing step was performed. Previous work for predicting fineness has techniques based on static analysis, and most do not intensify data cleaning and processing. In Mejić et al. [9], the operating ranges considered normal for each input variable were consulted with the process team to assist in the detection of outliers. In Stanišić et al. [8], the 3σ rule described by Pearson [13] was used to remove outliers, besides the analyses made on Mejić et al. [9]. The proposal made by Pani and Mohanta [7] expands the treatment of raw data and uses two more techniques: box plot and Hampel Identifier showed in Pearson [13]. Unlike these works, this paper approaches three methods for investigating anomalies based on statistical analysis: graphical analysis (histograms and scatter plots), standard score, box plot, and also Isolation Forest (IForest), proposed by Liu et al. [14].

After the graphical analysis, the standard score method, popularly known as z-score [15], was applied. Through this method, it is possible to identify outliers related to measurement problems of the installed physicals sensors such as malfunction, calibration, among other factors. For each input variable, the range of values considered as the regular operation was discussed with the plant's process team, observing historical data to assist in the detection of anomalies.

The information can be considered an outlier if the z-score (Z) is above 3 or below -3, that is, $|Z| > 3$, following the same formula and approach as the 3σ rule.

Next, the box plot was applied. It is a graphical tool used to evaluate the empirical distribution of data, providing a complementary means to analyze them. Descriptive statistics measures such as minimum, maximum, first, second, and the third quartile form the box plot [13].

Comparisons with previously used statistical analyses helped to identify and prove that certain information is an outlier. Besides the statistical and graphical analysis, this paper proposes the use of the IForest algorithm to assist in data processing.

Table 1 Input variables and their delay time

Variable Name	Unit	Notation	Delay (min)
Clinker flow rate	t/h	Clinker_rate	7
Slag flow rate	t/h	Slag_rate	7
Pozzolana flow rate	t/h	Pozzolana_rate	7
Gypsum flow rate	t/h	Gypsum_rate	7
Mill feed belt current	A	Mill_beltCurr	7
Mill fresh feed flow rate	t/h	Mill_frshFeed	7
Cement type	-	Cement_type	7
Fill level of chamber 1	%	Mill_lvCh1	7
Fill level of chamber 2	%	Mill_lvCh2	0
Mill main motor power	kWh	Mill_pwr	0
Mill main motor current	A	Mill_curr	0
Air pressure at mill inlet	mbar	Mill_pressIn	7
Air pressure at mill outlet	mbar	Mill_pressOut	0
Elevator current	A	Elev_curr	0
Rejects flow rate at separator outlet	A	Sep_rejects	0
Cement temperature on mill output	°C	Mill_cemT	0
Separator rotor speed	%	Sep_rtrSpd	0
Air pressure at separator outlet	mbar	Sep_pressOut	0
Filter differential pressure	mbar	Filter_difPress	0
Fan current	A	Fan_curr	0
Silo elevator current	A	Silo_elevCurr	0

This algorithm is based on the isolation of anomalies from the data set instead of considering information as irregular based on instances that do not present a normal profile. It does not use distance or density measurements to detect anomalies, which can be an advantage, as it eliminates the main computational costs [14].

IForest isolates information by randomly selecting a variable and then randomly selects a split value between the maximum and minimum values for that variable. This random partitioning will produce shorter tree paths in anomalous data, distinguishing them from the others, as an anomaly usually requires fewer partitions to be isolated. The partitions number needed to isolate a point is equivalent to the path length from the root node to a termination node. One way to detect anomalies is to classify data according to the path length or anomaly score. This score is calculated as follows:

$$S = 2 \frac{E(h(x))}{c(n)} \quad (1)$$

Where $h(x)$ is the path length of the point x , $E(h(x))$ is the average value of $h(x)$ for a set of isolated trees, n is the number of external nodes and $c(n)$ is the path length average that does not reach the point in the decision tree. How bigger the path length, how closer to 0 the score will be. So, if S is close to 1, x , very likely, will be an anomaly. However, if S is less than 0.5, x likely will be a normal value.

The mentioned techniques were applied separately to the data set. The detected outliers were removed or treated with value substitution in cooperation with the industry to avoid possible deterioration in the model's results [15]. The data were evaluated by determining the descriptive statistics such as minimum, maximum, average, standard deviation, skewness, and kurtosis values.

From that, the data set containing 700 results of cement fineness from laboratory analyses associated with the measurable variables of the grinding process was obtained. Next, these data were scaled by removing the median and scaling the data according to the interquartile range (IQR - Interval between the 75th and 25th percentiles). The median and the IQR generally provide better results in case there was still some type of outlier in the data set.

4. SUBSET SELECTION

The material that leaves the ball mill and enters the separator depends on the characteristics of the material that enters the mill and also on the grinding mill performance, which means that the process variables of all parts of the cement grinding circuit are potential inputs for online estimation of the cement fineness. Knowing all the stages of the process becomes essential to identify the variables that most impact the cement fineness. However, it needs caution to perform the separation of important from irrelevant information.

First, the input variables were chosen based on the study about the cement grinding process, in collaboration with the factory, as shown in Table 1. Then, the analysis of covariance between attributes using Spearman's rank correlation coefficient, often denoted by the ρ , was performed. While Pearson's coefficient, proposed by Pearson [16], assesses linear relationships correlation, Spearman's coefficient evaluates monotonous relationships, whether linear or not. A perfect Spearman's correlation of +1 or -1 occurs when each of the variables is an exact monotonous function of the other [11].

The subsets of input variables must contain relevant information from the cement grinding process to control the fineness. However, highly correlated attributes can difficult the training of the neural network due to the insertion of redundant information, increasing the complexity unnecessarily, and also the local minimums [8]. The use of the Spearman's coefficient made this analysis possible.

Next, the mutual information algorithm, based on information theory, was used to quantifies how much information about the output is given by every input signal. This method is sensitive to dependencies that are not shown in covariance. It quantifies the information set obtained about a random variable by observing other random variables [12]. The concept of MI is intrinsically associated with the entropy of a random variable, which is its degree of indeterminacy itself. MI can be expressed equivalently:

$$I(X, Y) = H(Y) - H(Y|X) \quad (2)$$

where $H(Y)$ is the entropy calculated for the variable Y and $H(Y|X)$ is the conditional entropy of X and Y . When there is no information about Y contained in X , $I(X, Y) = 0$. If the information contained in X completely defines Y and can be used to predict Y , the MI will be $I(X, Y) = 1$.

5. MODEL STRUCTURE

Backpropagation neural network models for predicting the cement fineness were designed as described below, based on the results of laboratory tests and the preprocessed input data, described in Section 3 and 4. The artificial neural network developed had one hidden layer with 80 neurons and used an ELU activation function, proposed by Clevert et al. [17]. The output layer used a linear activation function, described in Aurelien [10].

The choice of hyperparameters is one of the most critical decisions for the successful design of a backpropagation neural network. Unfortunately, there is no standard method for determining the ideal topology of a neural network. This is mainly decided by choosing the set of hyperparameters that produces the smallest prediction error. Both the empirical method and GridSearch allowed obtaining the appropriate hyperparameters set. GridSearch is a tool that performs an exhaustive search on the parameter values specified for an estimator [18].

Previous works presented the use of the Levenberg-Marquardt backpropagation algorithm for training. In the present work, the models were trained with the Adam algorithm, proposed by Kingma and Ba [19]. It is a stochastic optimization algorithm based on the gradient method and uses estimates of the first and second moments. It is considered computationally efficient and requires little memory. For this reason, and because it presented better results in the tests performed, this algorithm was used.

6. RESULTS

6.1 Input Selection

As the separation of coarse and fine particles is carried out in the separator by the interaction of drag forces, centrifuges, and the force of gravity, it is clear that the

airflow at the separator inlet and outlet and rotor speed are variables that contain fineness information.

A correlation between the variables Sep_rejects and Elev_curr can be identified from the process know-how, as the elevator provides information on the amount of material leaving the mill, and the rejects indicate the amount of material leaving the separator and returns to the mill or final product silo. Variable Sep_pressOut is equivalent to the pressure at the filter inlet, as it is located in front of the separator. Therefore, it will present a high correlation with the variable Filter_difPress. The variable Clinker_rate is the one that most impacts the variable Mill_frshFeed since the percentage of clinker inserted in the mill comprise the range of 70 to 90%. Spearman’s coefficient proved the high correlation between these variables, as shown in Table 2. Because of this, these input variables were separated into two distinct subsets.

Then, the MI algorithm was applied to quantify how much each input variable represents the fineness. The first subset of input variables was obtained from the variables Sep_rejects, Sep_pressOut, Mill_curr, and Clinker_rate. The results show that only these variables contain 74% of information about fineness. The second subset was obtained starting with Elev_curr, Filter_difPress, Mill_pwr, and Mill_frshFeed, following the same procedure performed for the first.

From the application of the MI algorithm and also in agreement with the factory process team, the variables Mill_cemT, Fan_curr, and Mill_pressIn were removed from both subsets as they did not directly impact the cement fineness.

A sensible approach to preserve information is to add information about the cement type being produced in each subset (Cement_type), in addition to the air pressure at the separator outlet (Sep_pressOut), once the fineness control strategy or the recipe may change.

Finally, two subsets of input variables were obtained, referred to as *subset 1* and *subset 2*, shown in Table 2. Both subsets, although different, contain the same amount of information on fineness: 98%.

Table 2 Subsets of input variables selected and their respective Spearman’s correlation

Subset 1	Subset 2	ρ
Sep_rejects	Elev_curr	0.90
Sep_pressOut	Filter_difPress	0.80
Mill_curr	Mill_pwr	0.99
Clinker_rate	Mill_frshFeed	0.81
Slag_rate	Slag_rate	-
Pozzolana_rate	Pozzolana_rate	-
Gypsum_rate	Gypsum_rate	-
Mill_lvCh1	Sep_pressOut	
Cement_type	Cement_type	-

6.2 Model Performance Evaluation

The mean square error (MSE) was used to evaluate the estimation quality of the models. It provides an idea of the number of errors generated by the model in its predictions:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

where n represents the number of instances in the data set, y_i is the vector that represents the laboratory values, and \hat{y}_i are the predicted values. Mean absolute error (MAE) was also used, as a complementary metric:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4)$$

6.3 Model Performance Results

Neural networks need to be trained to fit the model to the data. A common technique, and also the most used to divide the data set in previous works, was the use of a fraction of the data for training and the remainder for testing. However, these models tend to overfit, which reduces their accuracy when tested with more general data that were not in the model training set [10]. Therefore, from the data set containing 700 samples, the cross-validation method was used to train the models described in Pedregosa et al. [18]. By default, the number of divisions n chosen was 5.

A good model should have MAE and MSE values close to 0. To decide if the prediction errors obtained are acceptable, one must consider the application of the model. As the processes presented by Stanišić et al. [8] and Mejić et al. [9] are similar to *process 1*, comparisons of the results are feasible.

The results obtained from the two models are presented in Figures 2 and 3. Model 1 was based on *subset 1*, and model 2 based on *subset 2*.

In Stanišić et al. [8] and Mejić et al. [9], the authors reported, respectively, MSE values of 1.01 and 0.9 as soft sensor results for online cement fineness prediction in ball mills, while model 1 proposed in this work achieved MSE of 0.85 and 0.65 for the MAE.

Although model 2 performs well in the first samples, at the end of the test data set, it effectively lost the ability to predict, in addition to the fact that it presented a lower performance than model 1, based on the prediction error results shown in Table 3.

The laboratory tests of the factory, referring to *process 1*, show a standard deviation of $\pm 1\%$ in the fineness results. Thus, besides presenting better results than previous works, model 1 satisfies the basic requirements of acceptable error of estimate in this plant.

Table 3 Performance of the developed models

Model	MSE	MAE
1	0.85	0.65
2	1.15	0.80

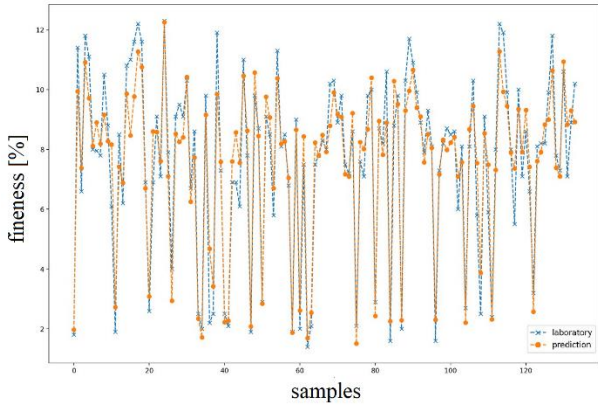


Figure 2 Comparison between the fineness obtained through laboratory results and the estimated by model 1 in the test data set of the subset 1

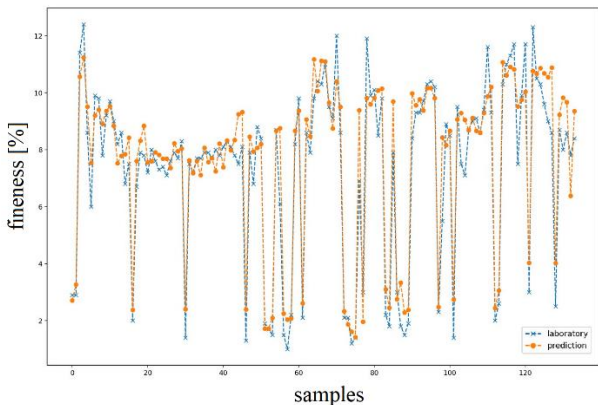


Figure 3 Comparison between the fineness obtained through laboratory results and the estimated by model 2 in the test data set of the subset 2

6.4 Soft Sensor Performance

The soft sensor developed based on model 1 was implemented at the factory for system validation. This test was carried out for 10 days during the cement production of process 1. The fineness was predicted by the soft sensor every 5 minutes and determined by the laboratory every 3 hours, on average, totaling 50 laboratory results.

Figure 4 depicts the excellent outcomes achieved by the soft sensor. These results demonstrate its robustness to detect fineness variation accurately. The soft sensor responds significantly before the laboratory results, as it quickly detects the variation of fineness during the process. Besides, this soft sensor was designed to estimate fineness in a

process that produces two cement types, which is a difference when compared to previous works in the area. Thus, this system is also able to immediately identify when the factory produces *cement type 1* or *cement type 2*. In cases where dosage related problems occur, the estimated fineness will represent a very different value compared to the desired one since this soft sensor takes into account each material in the cement recipe as an input variable. As these situations occur for a short period, operators do not control the fineness. Therefore, these noises have been eliminated from the graph. Noises related to moments near the start and stop of the mill were also eliminated from the graphic. The soft sensor is currently installed at the factory and is being used by operators. Thus, the operators can take corrective actions to maintain the desired fineness.

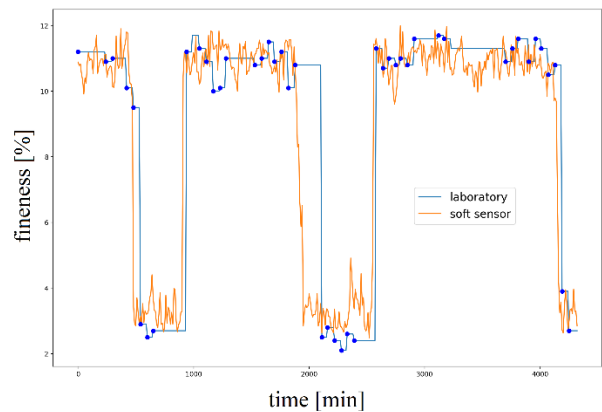


Figure 4 Online performance of implemented soft sensor based on model 1

7. CONCLUSIONS

This paper presents the research and the implementation of models based on neural networks as soft sensors for online prediction of cement fineness in the cement grinding process. The preprocessing of the raw data was carried out in an intensified way, which allowed the removal of inconsistent, redundant information, and also the scaling of characteristics. Two models based on a multi-layer perceptron neural network trained with the Adam algorithm were developed based on subsets of input variables obtained through the of the process know-how, use Spearman's coefficient and MI algorithm. Model 1, based on *subset 1*, showed excellent performance and was implemented as a soft sensor. The soft sensor was implemented in a real factory and was tested during the production of cement from *process 1* for 10 days. The laboratory tests performed after the soft sensor installation demonstrate the system's ability to predict fineness. Due to of lack of an online monitoring system, there is no control system in place for accurately controlling cement fineness in cements industries. Through the fineness estimation of this soft sensor, operators now can take appropriate corrective actions and eliminate situations that lead to cement production with inadequate

fineness. Thus, the online cement fineness predicting helps the process operation team to maintain the product quality, which will provide an improvement in the grinding process, with an increase in equipment efficiency, reduction of specific energy consumption, in addition to positive impacts on the environment. As the algorithm uses historical values of input variables and desired output, it can be applied to other types of industrial processes with continuous production.

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