Industrial Process Condition Forecasting Methodology based on Neo-Fuzzy Neuron and Self-Organizing Maps

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The condition forecasting of industrial processes represents a key factor to allow the future generation of industrial manufacturing plants. In this regard, this paper presents a novel soft-computing based methodology for the assessment of the current and future condition of industrial processes by the combination of Neo Fuzzy Neuron (NFN) and Self-Organizing Maps (SOM) data-driven based modelling. The proposed method models, individually, the critical signals describing the industrial process.

Keywords: Forecasting, Fuzzy neural networks, Industrial plants, Predictive models, Time series analysis

Introduction

Reliability and safety are becoming critical aspects in modern industry. In this regard, the industrial sector has made significant efforts toward process condition monitoring approaches in the last decade[1-4]. However, the condition forecasting of the industrial processes, although critical for allowing preventative actions, is still an open-problem in the field[5]. Thus, the combination of the future knowledge of the process status and the consequent assessment of the future condition is a necessary objective towards the next generation of industrial monitoring strategies[6-7]. Thus, the modelling of such signals represents a valuable source of information since it allows process condition assessment and the application of forecasting analyses[8-10]. In this work, a novel condition forecasting methodology for industrial process monitoring is proposed. The main contribution of this work lies on the proposal of a condition forecasting scheme that overcomes the accuracy and performance limitations of classical methods. The methodology was implemented and tested in the Copper Rod Manufacturing Process as an example for possible future extrapolation in industry.

Industrial Process Condition Forecasting

The proposed method for industrial process condition forecasting combines high-performance time series modelling, together with non-linear process information. Thus, the objective is to forecast industrial process condition by the modelling, forecasting and posterior non-linear combination of process critical signals. The diagram of the proposed method is shown in Figure 1. The method proceeds as follows: (i) the n identified critical signals are modelled by a set of n NFN based models in order to forecast its expected behavior in a predefined time horizon, (ii) the n forecasted signals are codified by means of a SOM based topology preservation mapping, that summarizes the n-dimensional map into the Matching Unit (MU) of the grid, that is, the operating point of the process, and, finally, (iii) the information regarding future condition and forecasting robustness is given by the assessment of the operating points into the resulting supervised mapping from the SOM training.

NFN based signal modelling

The objective of the models is to drive the n critical signals into a future time horizon, p. In this regard, the models present a multi-input single-output structure as shown in Eq. (1), where considering a target signal, $y(t)$, the model presents a single output that corresponds to a future value of the target signal, $y(t+p)$. The inputs of the model correspond to: (i) the current value of the target signal, y (t), (ii) a past value of the signal delayed z samples, $y(t-z_1)$. It must be noted that z_1 is set by means of an optimization

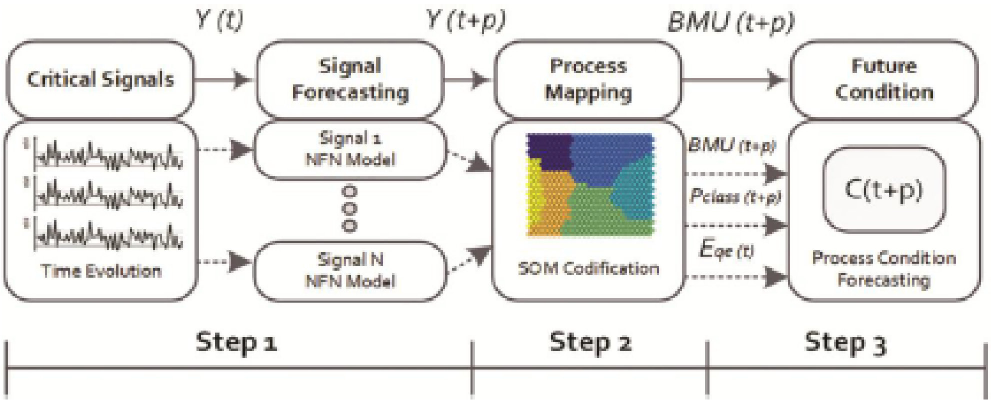

Fig. 1 — Block diagram of the proposed method. Three steps are identified in the diagram: (i) Step 1: Critical signals forecasting, (ii), Step 2: Process behavior codification, and (iii) Step 3: future process condition assessment

algorithm in regard with the achieved error. Finally, (iii) the mean value of the signal in the last 60 min, $\bar{y}(t)$. This input is calculated to provide information regarding low dynamics of the signal.

$$y(t+p) = NFN\left(y(t), y(t-z_1), \bar{y}\,(t)\right) \qquad \dots (1)$$

By the intrinsic architecture of the NFN, the number of synaptic nodes is equal to the number of inputs of the model, so there are $Sy=3$ synaptic nodes for each NFN model. The other configuration parameter of the NFN is related with the number of Membership Function (MF) associated to the description of each input, h. Increasing h improves the resolution of the algorithm, but also increases the number of weights to find during the training procedure, which increases complexity in modelling. For this application, h is set to 15 MF per input, which is a usual value within the *h=[5-20]* recommended interval. The defined structure of the NFN based model is the same for all *n* signals, however, the selection of the optimum *z* value is selected individually for each model. Performance of modelling is evaluated by classical error metrics. In this regard, the Root Mean Squared Error (RMSE), and the Mean Absolute Percentage Error (MAPE) for the number of fitted points (*L*), are used to evaluate the goodness of the modelling, which calculation procedure is presented in Eq. (2) and Eq. (3), respectively.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{L}\left(y(t)-\hat{y}\,(t)\right)^2}{L}} \qquad \dots (2)$$

$$MAPE = \frac{\sum_{t=1}^{L}\left|\frac{(y\,(t)-\hat{y}\,(t))}{y\,(t)}\right|}{L}\cdot 100\% \qquad \dots (3)$$

SOM based process behavior codification

The operating point of the process, BMU (t), is estimated by the SOM based combination of the *n* critical signals considered into the process operating point. Such combination is carried out by the projection of the *n*-dimensional input into the SOM grid, and corresponding best matching unit assignment. It should be noticed that a new observation of the n critical signals is considered an observation of the process. During the training procedure, the SOM adapts the coordinates of the grid units, that is, the weights of the neurons, to the topology described by the *n*-dimensional input space. Therefore, considering such information, SOM can be evaluated with the output of the forecasting models in order to retrieve the future process operating point of the industrial process, as represented in Eq. (4).

$$BMU(t+p) = SOM\left(y_1(t+p), \dots, y_N\,(t+p)\right) \qquad \dots (4)$$

Typically, the performance of SOM map is evaluated in terms topographic error, E_{top}, and average quantization error, E_{qe}, during the training stage. The topographic error represents the percentage of data vectors for which the first-BMU and the second-BMU are not adjacent units, and, average quantization error represents the average distance from each data vector to its BMU. High values of quantization error imply that the evaluated observation does not belong to the characteristic data density distribution modelled during the training of the grid. In this regard, the quantization can be understood as a measure of similarity between the initial knowledge used to train the method and the evaluated observation, and then, it can be associated to a probability value related with the forecasting outcome reliability.

Future condition assessment

After the training of the SOM grid, a label is assigned to each MU in regard with the targets of the training dataset. This assignation is made following a majority voting approach. Thus, for a new observation to be evaluated, a BMU will result from the SOM, and its associated label will reveal the class outcome. In order to provide a class membership degree, p_c, to the future condition, the center of each class in the input space is estimated, and the corresponding BMU, in terms of proximity to such classes' centers are identified. The proposed method associates the highest membership degree, $p_c = 1$, to the points that belongs to the BMUs representing the center of the class. Therefore, the membership degree is reduced, following a sigmoid function, as distance from the center is increased. Hence, for each new observation to be evaluated, the related p_c is estimated. Afterwards, the future process condition, $C\ (t{+}p)$, is estimated by the method applying Eq. (5). That is, future condition is given in regard with three parameters: *(i)* the estimated future process operating point, $BMU\ (t{+}p)$ and corresponding class, *(ii)* the distance to the center of the corresponding class, and *(iii)*, the quantization error, E_{qe}. It must be noted that the proposed quantization error included in the condition estimation is related with the current time instant, t, in order to gain robustness and reliability. Indeed, the quantization error, E_{qe}, and the distance to the class, p_c, are used as weighting factors over the condition forecasting outcome.

$$C(t+p) = \frac{Class(BMU(t+p)) - p_c(t+p)}{1 - E_q\ (t)} \qquad \dots (5)$$

Copper Rod Manufacturing Process (CRMP)

Indeed, the aim of the CRMP is to manufacture copper rod from a continuous casting process. The CRMP process is divided into five main elements: *(i)* The shaft furnace is a vertical natural gas fired furnace in charge of melting the input high purity copper cathodes. *(ii)* The holding furnace acts as a lung for the copper melting process, which aims to provide a constant flow of copper to the rest of the process. *(iii)* The tundish is a ceramic valve that controls the melted copper flow to the rest of the process. *(iv)* The casting wheel is in charge of solidifying the melted copper by a heat extraction process. It uses a water-cooled steel band that encloses the casting cavity in which the molten copper solidifies to form a raw rod. Both casting wheel and the steel enclosure are refrigerated by means of a water cooling circuit. *(v)* The roughing mill reduced the diameter of the raw copper rod to meet the specified diameter conditions fixed by the plant operators. Finally, the copper rod is coiled and packed giving the final manufacturing product. A detail of the monitored part of the process is shown in figure 2. Therefore, avoiding the inherent complexity of the process, the condition, and in consequence the quality of the manufactured copper, is summarized in regard to the probability of porosity apparition (cup-cone failures) in the final copper rod manufactured unit. The probability associated with the produced unit is estimated *a posteriori* by a manual quality inspection procedure. This inspection fixes a range of porosity probability that is summarized in a discrete quality label assigned to each unit. This range is defined as the probability to find cup-cone failures in the manufactured unit. In this regard, the predefined quality ratios correspond to: high quality, *Q1*, probability between 0 % and 25 % of porosity affectation, medium quality, *Q2*, between 25 % and 75% and low quality, *Q3*, between 75 % and 100%.

Results and Discussion

The results show the capabilities of the NFN-based modelling to fit properly all signals during both training and validation stages. Indeed, the results of the modelling show that, in terms of performance, the NFN achieves good results for the critical signals modeled. In this regard, the temperatures Tundish Temperature $T_{tu}\ (t)$ and Copper Rod Bar Temperature $T_{ba}\ (t)$ are the signals that achieve the lowest MAPE and RMSE errors, 7.81 % and 9.68%, respectively. This is due to smoother dynamics content in both signals in comparison with Casting Wheel Refrigeration Index $I_{cw}\ (t)$ and Total Water Flow

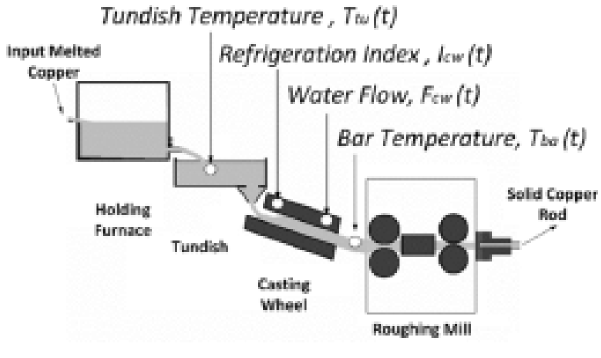

Fig. 2 — Copper Rod Manufacturing Process plant diagram. Critical signals considered are marked in the figure

Table 1 — Confusion matrix resulting on the assessment of the $C(t+p)$ with the proposed method

T \ P	1	2	3	Accuracy
1	43871 *95.57%*	1012 *2.21%*	1019 *2.22%*	95.37% *4.63%*
2	3197 *13.02%*	20624 *84.00%*	730 *2.97%*	84.00% *16.00%*
3	1151 *5.91%*	714 *3.67%*	17616 *90.43%*	90.43% *9.57%*
Accuracy	90.53% *9.47%*	92.97% *7.03%*	92.88% *7.12%*	91.30% *8.70%*

Casting Wheel F_{cw} *(t)*, which present sudden changes to response versus undesired deviations in the process. After modelling, all the forecasted signals are considered by means of an SOM-based mapping to define the operating point of the process, *BMU (t)*. Indeed, each BMU can be seen as a non-linear region of the space defined by the critical signals of the plant during the training stage. Such BMU summarizes all the variability of the signals in the corresponding region and is representative of the process operating condition at the evaluated time instant. The SOM grid has been configured by a hexagonal distribution 20 x 20, that is, a total of 400 units. The SOM is initialized and trained by a batch algorithm and a total amount of 150 epochs are performed. For this training set, the resulting errors are E_{qe} = 0.054 and E_{top} = 0.064. The obtained E_{qe} value corresponds to an average distance measurement among MUs. On the other hand, the low value of the E_{top} indicates that the initial topography is well preserved by the trained SOM, indicating with it the suitability of the projection. The T_{tu} *(t)* presents an almost uniform affectation. This is an expected behavior since it corresponds to the input temperature of the melted copper and presents greater stability. Similar behavior is appreciated in I_{cw} *(t)*, where a high heat extraction index causes small deviations towards the nominal condition of the process, causing a moderate probability of porosity in the final unit. On the other hand, T_{ba} *(t)*, presents nominal values, due to corresponds to the desired operating condition of the process. Finally, the information is combined by following Eq. (5) to obtain the future condition of the industrial process. In this regard, the performance on the assessment of the future condition is summarized in the confusion matrix exhibited in Table 1. The overall system achieves a performance of 91.30%, which corresponds to a notable performance result when dealing with real industrial data.

Conclusions

This paper presents a novel methodology for industrial condition forecasting applied to a real case study, a copper rod manufacturing process. The main contributions of the method are the adaption of neo fuzzy neuron-based modelling to forecast the critical process signals into a future time horizon and the future condition assessment approach by a non-linear mapping of those signals into the operating areas of the process with self-organizing maps. Regarding critical signal forecasting, it is demonstrated that neo fuzzy neuron-based modeling results in a suitable approach to capture and forecast the behavior of several industrial process signals with different natures and a similar range of dynamics information. Furthermore, self-organizing maps represent an enhanced approach to model non-linear behaviors defined by the available process signals and estimate the future process condition. Indeed, the resulting grid modelling emphasizes the expected underlying physical effects defined by the critical signals of the plant since the resulting data clusters matches with the copper porosity classes considered.

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