Nonlinear Simulator model Identification of a Walking Beam Furnace Using Recurrent Local Linear Neuro-Fuzzy Network

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Abstract

The walking beam furnace (WBF) plays a critical role in a steel production factory, and has complex nonlinear dynamic behaviour. Thus, using the conventional physical principles to build a model of the process leads to a time-consuming modeling procedure and when the number of operating set-points in walking beam furnace increases the conventional modeling problem difficultly will be solved, indeed analytical models cannot be applied or can not give satisfactory results. This paper proposes intelligent nonlinear simulator model for a real walking beam furnace in a steel production factory using nonlinear sub-system identification technique based on the recurrent local linear neuro-fuzzy (RLLNF) network. This model is trained using the local linear model tree (LOLIMOT) algorithm, which is a tree-structure divide-and-conquer algorithm. It is the first time that such nonlinear simulator (recurrent) model for a real WBF based on locally linear neuro-fuzzy modelling is developed. The recorded data of Iran Alloy Steel Company are used to identify and evaluate the RLLNF simulator model of walking beam furnace.

Keywords: *Walking beam furnace (WBF); System Identification; Recurrent local linear neuro-fuzzy model (RLLNF); Local linear model tree (LOLIMOT)*

1. Introduction

Walking beam furnace is one of the most crucial parts of a steel production factory which is a complex process within serial activities requiring technical support. Owing to physical reactions in WBF process, the WBF appears as a complex process that exhibits time varying and nonlinear behavior. Hence conventional modeling of such complicated process will lead to a tedious and time-consuming procedure even without achieving any appropriate solution. However, extracting a suitable model of WBF process seems to be necessary for the purposes of model-based control and diagnosis trials. In other words, proper simulator models are needed to test new controllers or new fault diagnosis methods which could be expensive or even impractical to be performed by experimental equipments.

Recently, a few attempts have been made to utilize data driven techniques to identify a proper model of WBF. An adaptive feed forward neural network (NN) which used prediction methods based on experimental data from a walking beam furnace was employed to temperature control of the furnace [1]. MIMO identification methods are presented to parameter estimation of dynamic model of a walking beam reheating furnace in [2]. Dynamic model of a walking beam reheating furnace based on a multilayer perceptron neural network which is trained using PSO algorithm is proposed in [3]. A kind of recurrent developed neural network called dynamic neural network was presented by the authors in [4], and each neuron of this model makes dynamism by incorporating feedback connections in it. The delayed outputs of each neuron are inputted to itself as additional inputs through weights.

Excluding aforementioned studies, according to author's best knowledge no attempt was made in order to propose a neuro- fuzzy (NF) simulator model of the WBF process. In our study, the simulator of WBF system is proposed for the first time. All the previous intelligent methods for modeling of WBF were on the basis of neural networks. However, the main drawback of neural networks is that systems cannot be expressed in them because they are usually considered as black-box models. Neuro-fuzzy modeling can be regarded as a grey-box technique on the boundary between neural networks and qualitative fuzzy models which system is expressible in fuzzy rules with using fuzzy modeling. The most common NF systems are based on two types of fuzzy models, TSK and Mamdani, combined with NN learning algorithms. But the TSK-type neuro-fuzzy model is preferable when the accuracy of the model represents the main concern [5].

Generally, TSK model exhibits better performance than other structures because of exploiting several local linear models when coping with nonlinear modeling. In this paper, local linear neuro-fuzzy (LLNF) models simply interpreted as TSK-type neuro fuzzy models are employed to deal with nonlinear and complex characteristics of WBF. In order to realize the dynamic behavior of the WBF by means of the model, the LLNF network is recurred.

The rest of the paper is organized as follows: In Section 2 an overview of walking furnace is presented, section 3 introduces the preprocessing and data mining of signals, in Section 4 the dynamic identification technique based on simulation technique has been explained, Identification of WBF using LLNF models with LOLIMOT learning algorithm and selecting the proper number of inputs to network are included in Sections 4.1, 4.2, respectively. The obtained experimental modeling results are presented in Section 5. Finally, the conclusions are drawn in Section 6.

2. Walking Beam Furnace in Steel Production

Iran Alloy Steel Company located at 30 km far from the Yazd, the city in the center of the Iran, was founded in 1999 and is one of the biggest steel production factories in Middle East and Iran. The factory consists of several parts such as steel production units, thermal and supplements operation, heavy and light rolling and, etc. In this paper subsystem modeling of walking beam furnace in light rolling is taken into account. The walking beam furnace is the major part of a steel production factory and plays a critical role in high quality of steel products, so as real time technical supports are required for better performance of it. Walking beam furnace is an industrial plant that serves to heat the inlet slabs coming from other parts of the factory. In the furnace, all slabs are heated to reach a predefined discharging temperature (1300C^o) and balancing of temperature distribution in slabs.

The structure of the walking beam reheating furnace discussed in following sections is shown in Figure 1. Slabs in the furnace move from tail zone to soaking zone. The control area of the furnace is divided into four temperature zones, which are denoted as zone1 to zone4 respectively. Recuperator zone is not a control area and has no fuel input. The slabs are heated by waste gas in this area. The function of preheating and heating zones is to heat a slab. The aim of soaking zone is to adjust the temperature gradient so that the inner temperature and surface temperature of the slabs can reach a balance. The FFB (Fuel Flexible Burner) burners provide the desired temperature of the furnace. FFB is a fabricated burner designed for heavy duty services and for preheated combustion air. There are 8 burners type FFB9 on preheating zone, 12 burners type FFB6 on heating zone 1, 8 burners type FFB9 on heating zone 2, 8 burners type FFB9 in soaking zone, All the burners are mounted on the furnace roof. The four zones are equipped with their own burners, while the recuperative zone is not equipped with burner and utilities the existing temperature in the fume of the combustion, coming from the front areas. Pressure of the furnace is controlled by a butterfly damper that fixed in exhaust, there are two hydro motors that set the damper angle, and a pressure sensor that measure the pressure of the furnace located in recuperator zone. The furnace temperature controlled with flow control valves and they set the fuel and air ratio that enter to burners.

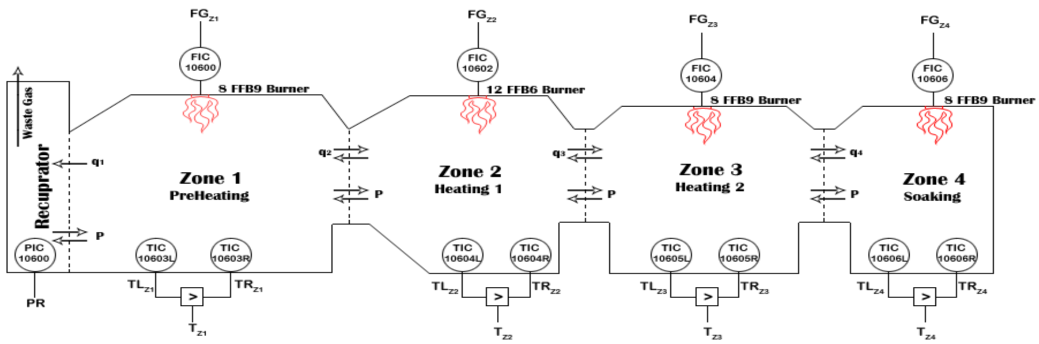


Figure 1. Structure of a Walking Beam Reheating Furnace.

For measuring the temperature of these zones, there are two sets of thermocouple that installed in right and left of each zone. The maximum temperature of these sensors will be referenced of controlling the fuel. Significant process variables are measured by correspondent sensors at pre-chosen points of walking beam furnace and then acquired data are recorded in monitoring data access system. Technical description and nomenclature of furnace variables used in Figure 1 are given in Table 1.

Table 1. Walking Beam Furnace Variable Descriptions

Zone Name	Variable Name	Unit	P&ID Name	Description
Pre heating	T_{LZ1}	C^o	TIC10603L	Left temperature of zone 1
Pre heating	T_{RZ1}	C^o	TIC10603R	Left temperature of zone 1
Pre heating	F_{Gz1}	NM^3/h	FIC10600	Gas flow of zone 1
Heating 1	T_{LZ2}	C^o	TIC10604L	Left temperature of zone 2
Heating 1	T_{RZ2}	C^o	TIC10604R	Left temperature of zone 2
Heating 1	F_{Gz2}	NM^3/h	FIC10602	Gas flow of zone 2
Heating 2	T_{LZ3}	C^o	TIC10605L	Left temperature of zone 3
Heating 2	T_{RZ3}	C^o	TIC10605R	Left temperature of zone 3
Heating 2	F_{Gz3}	NM^3/h	FIC10604	Gas flow of zone 3
Soaking	T_{LZ4}	C^o	TIC10606L	Left temperature of zone 4
Soaking	T_{RZ4}	C^o	TIC10606R	Left temperature of zone 4
Soaking	F_{Gz4}	NM^3/h	FIC10606	Gas flow of zone 4
Recuperator	PR	bar	PIC10600	Furnace Pressure

3. Data Mining for System Identification

The procedure of data driven system modeling can be briefed in four phases:

1) Collect uncorrupted and valid Input-Output data
2) Select suitable model structure
3) Estimate the model parameters
4) Model validation

One of the most important assumptions to get valid information from an input and an output is that the changes happened in the output are affected by the system input and not disturbance or noise [7]. Hence data mining methods are required in order to extract valid data from the available data. In the following sections, the procedure of data mining is suitable for discussion about of valid data extraction.

To identify a model for plant, the collected data for identification should be reliable in order to illustrate various dynamics of the system. Owing to safety and limited access to real WBF, we could not feed various signals with different frequencies to the system. According to system identification theory which emphasizes on using powerful signals such as PRBS to excite all dynamics of the system, we have to exploit the available data from normal operating conditions which leads to a passive identification approach.

The first step for preparing the simulator model is gathering the WBF subsystems data from different zones. The zone's data are recorded in data access system (at the control room of the company) that is easily accessible. This experimental real data is sampled in a 23-day period (from 7th to 29 July 2010) with 5 second interval. Additionally, %50 of sampled data are used as training set and rest of them as checking data (i.e. 20% as test set and the rest as validation set).

After discussion with process engineers and operators of the factory, we made an effort to remove faulty operational points from available gathered data sets. Additionally, due to uncontrolled effects such as noises and disturbances acting on the process, one should try to use some pre-processing methods presented in identification references [7] such as peak shaving and normalization.

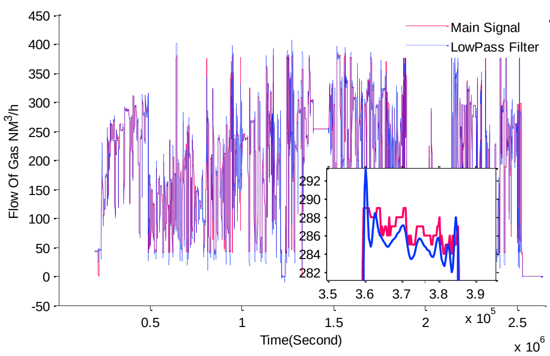
Peak shaving and smoothing intensive changes in data are very important for pre-processing methods. These commonplace abrupt changes may occur due to the operation of sensors or data acquisition cards. They cause some numerical problems in measuring and recording variables as well [7]. This may happen because the sensor is turned off for instance, when it needs to substitution or repaired. These sudden changes have a lot of energy in high frequency rang that degrades estimation of the models parameters or validity rate [12]. To cope with this problem, the data are passed through a low frequency band pass filter that can eliminate noise signal from the original signal. For instance, Figure 2 shows how a low frequency band pass filter affects the original flow signal $F_{GZ3}(t)$. As it can be seen low band pass filter can effectively eliminate noise signals from the $F_{GZ3}(t)$.

Since the inputs and outputs data have different ranges that cause error in data quantization and the system badly identified [7], data normalization must be accomplished as an important step of data mining. Experiments have proven that, more promising results will appear using data normalization.

The normalized of the signal X is given as X_N by:

$$X_N = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad (1)$$

Where X_{min}, X_{max} are minimum and maximum values of X respectively. Figure 3 shows the F_{GZ3} signal before and after normalization according to eq. (1).



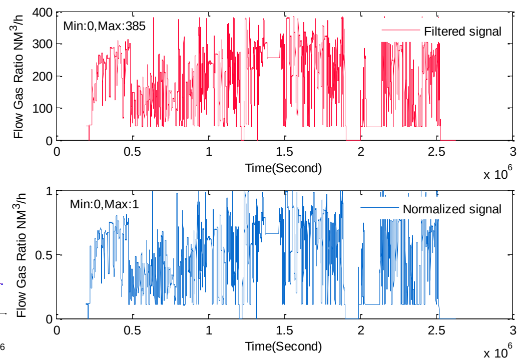


Figure 2. F_{GZ3} signal with noise cancelation. Figure 3. F_{GZ3} signal with normalization.

4. Dynamic Identification Based on Simulation Techniques

Dynamic nonlinear systems can be modeled for exploiting two techniques so-called simulation and predictions. Both methods employed static (memory-less) models such as static neural networks in their architectures.

Since static models are not capable enough for modeling a nonlinear dynamic process, adding dynamics (memory) to the static model architecture is essential in order to cover the whole dynamic behavior of the real process. Simulator and predictor models differ in terms of the way dynamics have been introduced into the static model architecture. Figure 4 shows the structure of both predictor and simulator models utilized for nonlinear dynamic identification. Both structure exploit tapped delay lines (TDLs) together with a nonlinear static model. TDLs are used to generate the delayed inputs and outputs. Then, these delayed inputs and outputs are fed in to the static nonlinear architecture due to add memory to the entire model. In this paper, simulation models are employed for identifying a simulator model of the real walking beam furnace. As it can be seen in simulator model of the walking beam furnace the output of the model, but not the real plant output, at a moment is applied as its input at the next moment. Such model is also called recurrent model.

4.1. Identification of Simulator Model Using Recurrent Local Linear Neuro- Fuzzy Network

In order to identify the simulator model of the walking furnace, passive identification approach is considered. According to the system identification theory, simplest solution should be utilized to build the model of plant. It was mathematically proven that the least square error (LSE) method is the optimum modeling method in the case of linear systems [6, 11]. In this case, if satisfactory results were not achieved by exploiting such method then it can be concluded that the plant is of nonlinear process. Since the furnace consists of four zones, each zone is considered as a sub-system and then correspondent sub-model of each zone is identified. Finally, in order to construct an overall simulator model of the furnace, all of four constructed sub-models of zones are integrated in a serial-parallel structure. In the preceding section, the general conceptual structure of a simulator model was described. In order to identify a simulator model for walking beam furnace (WBF), recurrent local linear neuro-fuzzy network is utilized and local linear model tree algorithm is employed to find the best structure and parameters of the network, as well. The major reason of exploiting RLLNF models trained by LOLIMOT algorithm can be abbreviated as follows:

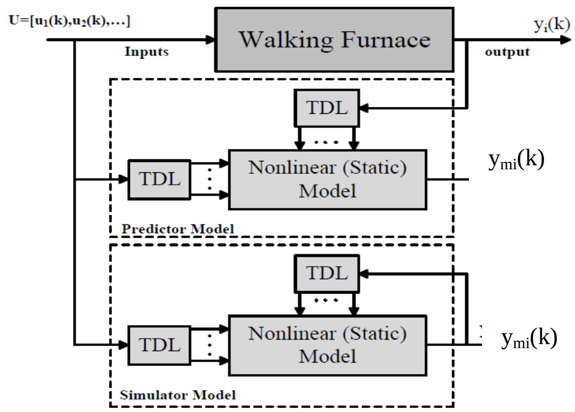


Figure 4. General Structures of Simulator and Predictor Models.

Low computational expense due to local estimation, robustness with respect to noise due to regularization effect, high accuracy, online adaptation. There are also so many other advantageous of RLLNF models which can be found in [10].

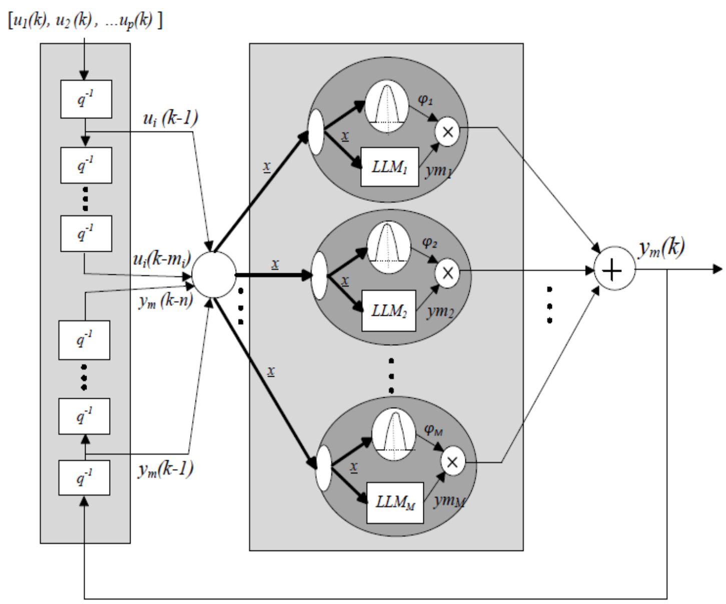


Figure 5. Architecture of Recurrent Local Linear Neuro-fuzzy Network

The structure of the recurrent local linear neuro fuzzy network is depicted in Figure 5 each neuron realizes Local Linear Model (LLM) and an associated validity function that determines the region of validity of the LLM. The LLNF model can be easily interpreted as Takagi-Sugeno (TS) model, whereas, each neuron represents one rule, and the validity functions represent the rule premise and the LLMs represent the rule consequents.

As it was discussed in previous section, to build a simulator model the delayed inputs of the process as well as the past samples of the LLNF model output should feed in to the model as inputs. Hence in the case of dynamic LLNF the input of the model is given as:

$$\underline{x} = \left[u_1(k), u_1(k), \ldots, u_p(k), y_m(k)\right]^T \tag{2}$$

Where $u_i(k)$ comprised of the previous values of input i using TDLs such that:

$$u_i(k) = \left[u_i(k-1), u_i(k-2), \cdots, u_i(k-m_i)\right] \tag{3}$$

And, $\hat{y}(k)$ contains the delayed samples of the LLNF output as follows:

$$y_m(k) = \left[y_m(k-1), y_m(k-2), \ldots, y_m(k-n)\right] \tag{4}$$

n and m_i(i=1,…p) are the denominator and numerator orders of the i-th input, respectively.

The parameters w_j of j-th rule consequence:

$$\underline{w}_j = [b_{j_{11}} b_{j_{12}} \cdots b_{j_{1m_1}} \cdots b_{j_{p1}} b_{j_{p2}} \cdots b_{j_{pm_p}} \cdots a_{j_1} a_{j_1} \cdots a_{j_n}]^T \tag{5}$$

Are estimated employing the weighted least square (WLS) solution [10].

Hence, the global output of the model is calculated as the weighted summation of the output of all LLMs as follows:

$$y_m(k) = \sum_{j=1}^{M} \sum_{i=1}^{P} \Big[b_{j_{i_1}} u_i(k-1) + b_{j_{i_2}} u_i(k-2) + \ldots + b_{j_{i_m}} u_i(k-m_i) - a_{j_1} y_m(k-1) - a_{j_2} y_m(k-2) - \ldots - a_{j_n} y_m(k-n) + \xi_i \Big] \varphi_j(x) \tag{6}$$

Where $b_{j_{i m_j}}$ and a_{in} are represent the numerator and denominator coefficients, and ζ_j is the offset of the LLMj. $\varphi_j(x)$ are the operating point dependent weighting factors. In the other words, network interpolates between different LLMs with the validity functions [10].

The validity functions on x are typically chosen as normalized Gaussians so they form a partition of unity as:

$$\sum_{j=1}^{M} \varphi_j(\underline{x}) = 1 \tag{7}$$

In the case of axis-orthogonal Gaussians, the validity functions are defined as:

$$\varphi_j(\underline{x}) = \frac{\mu_j(\underline{x})}{\sum_{j=1}^{M} \mu_j(x)} \tag{8}$$

Thus, $\mu_j(x)$ can be given as:

$$\mu_j(\underline{x}) = \exp\left(-\frac{1}{2}\left(\left(\frac{x_1 - c_{j_1}}{\sigma_{j_1}}\right)^2 + \ldots + \left(\frac{x_D - c_{j_D}}{\sigma_{j_D}}\right)^2\right)\right) \tag{11}$$

With $D = n + \sum_{i=1}^{p} m_i$ as the total number of input channels of LLNF, and c, σ are the center coordinate and the dimensional individual standard deviation, respectively.

A complex WBF model divided into a number of smaller and thus simpler sub-problems, which are solved independently by identifying simple linear models [10, 13]. The most important factor for the success of this approach is the division strategy for the original complex problem that this will be done by an algorithm named LOLIMOT (Locally Linear Model Tree). LOLIMOT is an incremental tree construction algorithm that partitions the input space by axis-orthogonal splits [10].

The LOLIMOT algorithm consists of an outer loop in which the rule premise structure is determined and a nested inner loop in which the rule consequent parameters are optimized by local estimation. This loop can be summarized as a five step algorithm models [10, 13]:

Step1: Start with an initial model

***Step*2**: Find worst locally linear model which has maximum local loss function.

***Step*3**: Check all hyper-rectangles to split (through).

3a. Construction of the multi-dimensional Fuzzy membership Functions for both hyper rectangles.

3b. Construction of all validity functions.

3c. Local estimation of the rule consequent parameters for both newly generated LLMs.

3d. Calculation of the loss functions for the current overall model.

***Step*4**: Find best division (the best of the alternatives checked in Step 3, and increment the number of LLMs: $M \rightarrow M+1$).

***Step*5**: Test for convergence.

For the termination criterion various options exist, e.g. a maximal model complexity that is a maximal number of LLMs can be used.

4.2. Selection of Proper Number of Inputs for RLLNF Network

Identification process relies on the inputs with enough information and dynamism. In order to determine the proper inputs of the network, it is necessary to know that each input has its own particular duration of effect on the output. The problem of order determination for nonlinear dynamic systems is still not satisfactorily solved. Methods based upon higher order correlation could be used for order determination problem but these approaches are merely model validation tools that require building a model with a specific order first and then indicating which information may be missing [10]. In our work, selection of dynamic order of the models is performed by a combination of trial and error during the identification procedure and prior knowledge about the furnace. The suitable numbers of dynamics used for identification are presented in

Table 22.

Table 2. Numbers of Dynamics Used for Identification.

		Dynamics Depth			
		$That_{Z4}$	$That_{Z3}$	$That_{Z2}$	$That_{Z1}$
Variables	FGZ1	-	-	-	3
	FGZ2	-	-	2	-
	FGZ3	-	4	-	-
	FGZ4	2	-	-	-
	ThatZ1	-	-	1	2
	ThatZ2	-	1	4	1
	ThatZ3	1	3	1	-
	ThatZ4	3	1	-	-
	PR	3	1	1	2

5. Experimental Modeling Results

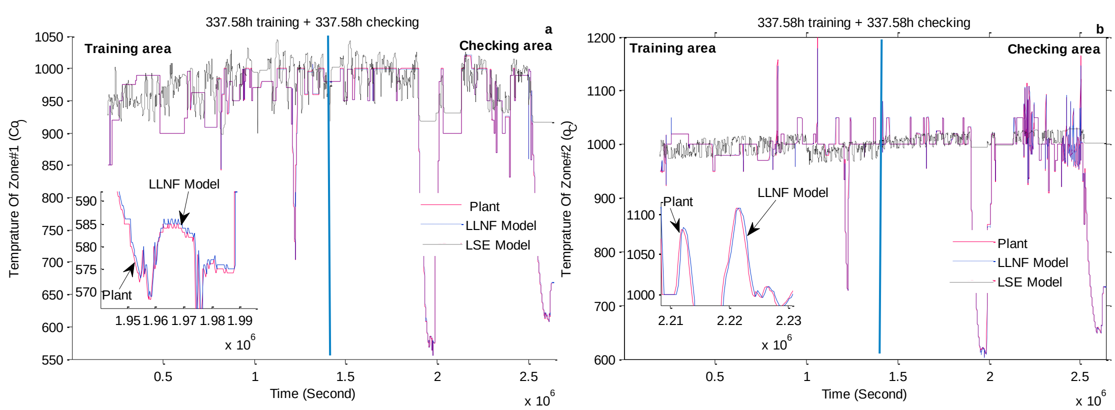
In this section, simulation results of the recurrent local linear neuro-fuzzy approach for modeling of each heating sub-system of the walking beam furnace as well as modeling of whole integrated furnace plant is presented.

In the case of locally linear modeling, selection of rules number is the greatest area of concern. Selecting large number of rules may lead to over parameterization and model complexity problems. In our research, number of neurons (rules) in each RLLNF network is increased until more neurons do not have a significant effects on the reduction of the mean square error (MSE) for the test data. Because of four heating zones existence, four RLLNF models are developed for these four zones with normal operating conditions. Hence the proposed model WBF has four serial neuro-fuzzy networks.

Figure 6 illustrates the outlet temperature of first zone, obtained from recorded data of the actual plant along with the responses obtained from both LSE and neuro-fuzzy models for both training and checking data sets. With a glance, one could simply conclude that LSE-based modeling method has severe problem in modeling of the first heating zone, while the RLLNF model demonstrates more accurate behavior, in the sense that, its response is closer to the response of the actual sub-system. Thus, including the LSE as the optimum modeling method for linear systems, the obtained results confirm that first heating zone of the furnace is of nonlinear plants. Figure 6-a, b, c show the model performances of the rest of three heating zones of furnace on the basis of both LLNF LSE techniques. Moreover, the number of rules obtained through the simulation procedure of neuro-fuzzy networks and corresponded MSE are given in Table 3.

Table 3. Number of Rules and Mean Square Error of each RLLNF Model.

	Number of rules	MSE Validation	MSE Train
LLNF(1)-Zone1	10	$5.33639e^{-5}$	$8.42250e^{-5}$
LLNF(2)-Zone2	8	$6.24164e^{-5}$	$2.69321e^{-5}$
LLNF(3)-Zone3	10	$8.97231e^{-5}$	$4.98129e^{-5}$
LLNF(4)-Zone4	10	$8.94030e^{-5}$	$3.75906e^{-5}$



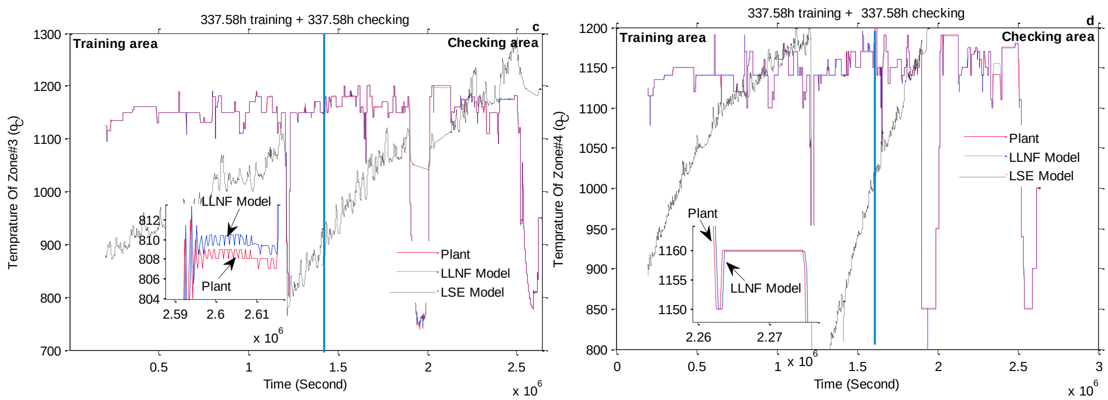


Figure 6. RLLNF Models Performance for Temperature of All Zones.

6. Conclusion

In this paper, local linear neuro-fuzzy modeling was carried out for a walking beam furnace in a steel production process, including four heating sub-systems. Finally all these models are integrated as a total modular simulator model. According the experimental results, all neuro fuzzy sub-models demonstrate high accuracy in the sense that they can effectively to create a faithful replica of their correspondent sub-systems. Besides, comparative study between LSE modeling result and neuro-fuzzy modeling proved that all of the heating subsystems exhibit nonlinearity within their behavior. Employing this modular simulator model in model based fault detection and isolation application as well as model based control looks to be a worthwhile direction for future research. More over developing a predictor model of the waling furnace could be also another further research contribution.

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