

RADIAL BASIS FUNCTION NEURAL NETWORK ALGORITHM FOR IDENTIFICATION SYSTEM OF WASTE HEAT BOILER UNIT

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Abstract

The Waste Heat Boiler (WHB) System is a steam-generating heat system that harnesses the energy transfer from combustion to transform water into steam, serving as the primary output. Identifying the plant model of the WHB unit poses challenges due to its dynamic characteristics and nonlinear behaviour, which are susceptible to the influence of numerous factors. This study involves the implementation of experiments aimed at identifying and collecting input data are boiler feed water flow and steam product flow, and its output is the real-time water level in high pressure drum from the operational activities of a fertilizer factory located in Gresik, East Java. The application of the Radial Basis Function-Neural Network (RBFNN) identifier is justified in identifying the dynamics of a WHB system due to its favourable approximation properties and straightforward topological structure. The optimal topology for the single hidden layer structure RBFNN model with learning rate 0.5 involves using five identifier input vectors and nine RBF nodes in the hidden layer, resulting Normalized Square Root Mean Square Error (NSRMSE) values of 0.2299. The minimal final prediction error also indicates indicate that the output of the RBFNN model is capable of accurately estimating the dynamic characteristics of actual measurements.

Keywords: Identification system, Level, Neural network, Radial basis function, Waste heat boiler

1. Introduction

The boiler is important as a utility unit inside fertilizer and petrochemical companies, exemplified by its utilization in PT Petrokimia Gresik. The primary purpose of the boiler is to provide thermal energy in the form of hot steam and transfer this energy to the steam turbine. The primary product, particularly in steam production, is utilized in subsequent stages within the ammonia plant and urea process units. The plant employs a Waste Heat Boiler (WHB) unit to meet its steam heat energy requirements, using exhaust gas from a gas turbine. The WHB system refers to a steam generator heat system that effectively exploits the transfer of energy from combustion to transform water into steam, serving as the primary output [1]. The steam generated will facilitate the process and provide the necessary power for the rotating steam machinery, often known as a steam turbine [1-3]. The absence of steam of high quality can cause harm to the rotating machinery. A waste heat boiler (WHB) is a specific boiler that exhibits high exhaust gas flow properties derived from gas turbines operating at low temperatures. Approximately 60% of the heat produced through combustion in the gas turbine is effectively utilized by the waste heat boiler (WHB) to facilitate the generation of steam.

It is essential to effectively regulate numerous parameters to produce high-quality steam, considering the dynamic features that frequently fluctuate in response to the prevailing process load. The initial stage in developing a control system, particularly one that relies on a plant model, involves modelling the system to ascertain its inherent properties. One approach that might be employed is the identification system methodology. It is challenging to identify and determine the mathematical model for a highly nonlinear and tightly linked complex system due to its dynamic properties. To address this challenge, an alternative strategy involves constructing models based on collected or observed data. An experiment was conducted to acquire real-time input and output data from a Gresik, East Java, Indonesia fertilizer factory. A mathematical model of a dynamic system can be derived through two distinct pathways. The initial methodology is grounded in the principles of natural law, while the alternative approach relies on empirical evidence. System identification refers to the discipline encompassing the artistic and scientific aspects of constructing mathematical models for dynamic systems based on the analysis of observed input-output data [4].

The initial stage in developing a control system, particularly one that relies on a plant model, involves the creation of a model for the system to ascertain its inherent properties [5, 6]. One approach that might be employed is the identification system methodology. The impetus for studying systems identification approaches arises from the inherent challenge of mathematically expressing a physical system, as the equations that describe the system's dynamics are often unknown. The influence of several factors, such as the attributes and intricacy of the system, temporal limitations, and accessible resources, significantly impacts the outcome. This observation is supported by previous research [7].

System identification is a methodology that intelligently chooses a suitable model and dynamically estimates the model parameters. This is done to ensure that the model's output closely approximates the response of the actual system when subjected to the same input signal. System identification encompasses more than just examining model studies and system features; it can also predict process behaviour and develop efficient control systems [8, 9]. A research investigation has been conducted using a theoretical

framework, where one potential methodology involves using artificial neural networks (ANN). Neural networks can acquire knowledge and adjust their behaviour based on a sequence of input and output data. Alternative neural network methodologies are widely utilized in various identification and control systems, including mathematical modelling and control system design for linear and nonlinear systems [8, 10, 11]. Artificial neural networks present a promising resolution for real engineering issues requiring intricate data processing. These networks exhibit a resilient nature and possess the capacity to model highly nonlinear and multivariate systems [8] accurately. The capabilities of artificial neural networks in various applications have been applied in areas such as control engineering [12], medical science [13] and character recognition [14, 15].

In contrast, several research studies have been conducted exploring the integration of artificial neural networks and radial basis functions as neurons in the hidden layer. These studies encompass various applications such as forecasting [8, 9], data mining [10], motor speed regulation [9], aircraft control prediction models [16], identification of nonlinear systems [7, 10, 17], and temperature regulation. Several authors [2, 17, 18] have demonstrated that the RBFNN identifier is a viable alternative for approximation in identification systems. This is due to its simpler topological structure, faster learning capabilities, and the availability of easy-to-implement methods [19]. Alitash and Salau [20] has also successfully applied RBFNN to identify multi-input multi-output (MIMO) boiler systems for temperature and pressure model and level water drum, but the network structure used 3 hidden layers so that this affects the complexity of the computational algorithm and a more complex network structure.

This study proposes an alternative model estimation for the waste heat boiler system using the Radial Basis Function-Neural Network (RBFNN) identifier. This choice is motivated by the RBFNN's advantageous features, including its faster learning capacity, ability to universally approximate, and capability to approach any nonlinear function [11, 21-23]. System identification refers to the discipline that encompasses both the artistic and scientific aspects of constructing mathematical models for dynamic systems based on observed input-output data [4]. The rationale behind investigating system identification techniques arises from the inherent challenge of accurately representing a physical system. Often, the equations that govern the dynamics of these systems are unknown and attempts to derive them would be impractical due to various constraints such as time, resources, safety, and cost [4, 11, 18].

One of the important parameters is the water level in the High-Pressure Steam Drum (HP drum). The water level affects the safety of the boiler process continuity. If the water level is too high, the steam produced will be too wet so that it has the potential to damage the equipment that utilizes the steam in its process utility. Conversely, if the water level in the WHB is too low, the components of the boiler tubes with high temperature heating will overheat, shortening the life of the boiler. Therefore, by considering safety and risk and in order not to interfere with the continuity of the process, the water level in the HP drum needs to be controlled at a certain height. In designing a control system, especially one based on a plant model, it is necessary to model the system with an input output data approach or known as system identification to determine the characteristics of the system. In of the single hidden layer radial basis function neural network architecture. This architecture has a simple network topology, adaptive learning process capabilities, and the ability to capture the characteristics of non-linear systems.

2. Waste Heat Boiler Identification System with Radial Basis Function Neural Network Approach

2.1. Waste heat boiler unit

The diagram illustrates the various stages involved in a particular process. Figure 1 displays the WHB system derived from the Exhaust Gas PT. Petrochemical Gresik No. 55012/6200 is represented using piping and instrument diagrams (P and ID). The system operates on the idea of processing waste heat boilers (WHB), where about 60% to 70% of the heat produced through combustion in the gas turbine is utilized by the WHB to facilitate steam generation [5, 24]. The primary output, vapor, is used in the ammonia and urea production facilities. In conjunction with the emission of exhaust gas from the gas turbine, the primary component introduced into the boiler system is regulated boiler feed water, commonly called boiler feed water (BFW). The BFW (boiler feed water) will be introduced into the system by the condensate pump P2221A WHB/B and directed into the low-pressure (LP) drum through the deaerator. The LP drum is also linked to the LP evaporator, which elevates the water's temperature within the drum, facilitating its transformation into steam through evaporation.

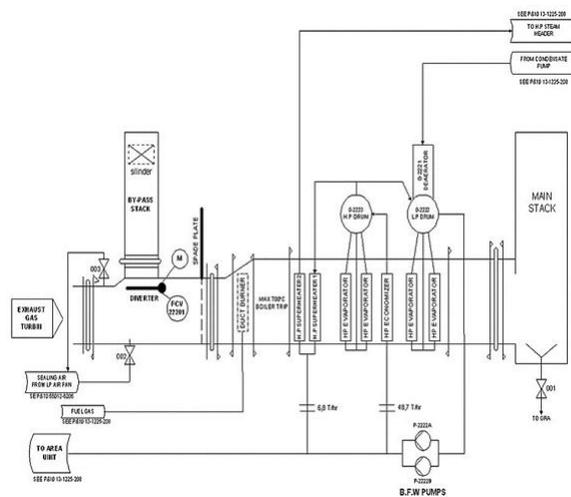


Fig. 1. Schematic P & ID (exhaust gas waste heat boiler system).

The internal and repetitive circulation process between the LP and LP evaporator drum facilitates the attainment of saturation temperature by the steam generated from the BFW in the deaerator. Nevertheless, in cases where the saturation temperature remains inadequate for generating the LP steam drum, it is imperative to provide supplementary steam from the high-pressure (HP) drum. Saturated steam in the LP drum will exit the drum and be transported back to the economizer by the action of pump BFW P2222 A/B. Under similar circumstances to those observed in an LP drum, the HP drum is similarly linked to the high-pressure (HP) evaporator, serving an identical purpose. In addition, using the HP steam drum facilitates the maintenance of a consistently high temperature in the superheater, hence ensuring the attainment of the necessary steam temperature. This is crucial for efficiently operating the system's waste heat boiler (WHB) and regulating steam flow and pressure.

The implementation of experimental design in the WHB system is conducted with meticulous attention to various factors, including security, safety, cost,

availability of equipment and measuring instruments for each variable measurement in the plant, as well as the limitations and constraints associated with the operation area of measurement [24].

2.2. Artificial neural network (ANN)

The utilization of artificial neural networks (ANN) has shown significant growth, extending its reach to various interdisciplinary domains. Artificial Neural Networks (ANNs) find many applications across several disciplines, such as computer science, engineering (including electrical, civil, mechanical, and aeronautical), medical science, environmental engineering, and business [25, 26]. The neural network architecture comprises a singular layer encompassing input, processing, and output elements. The quantity of layers is contingent upon the intricacy of the problem to be resolved. Evaluating neurons in an Artificial Neural Network (ANN) involves the utilization of feed-forward and backpropagation training techniques to address errors, as depicted in Fig. 2. The utilization of both algorithms is intended to provide optimal outcomes from a given set of training data. The artificial neural network (ANN) undergoes a network cycle consisting of four primary steps: (i) initialization, (ii) activation, (iii) weight training, and (iv) iteration [27, 28].

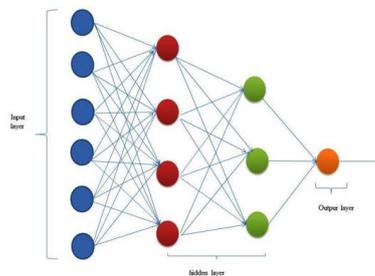


Fig. 2. Feed-forward neural network [5].

Artificial Neural Networks (ANNs) are utilized to acquire knowledge about mapping nonlinear input spaces to output spaces. The radial basis neural network (RBFNN) algorithm has gained significant popularity due to its extensive application in problem-solving. The network possesses a rapid linear learning algorithm that enables the construction of intricate nonlinear mappings [23, 29]. The Radial Basis Function Neural Network (RBFNN) design consists of three layers: an input layer, a hidden layer, and an output layer [21], as depicted in Fig. 3.

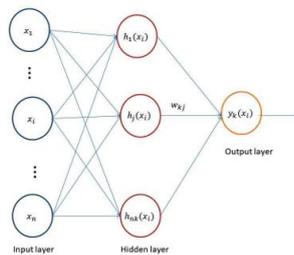


Fig. 3. Single hidden layer of RBFNN architecture [6].

2.3. Identification system

The main objective of the identification system is to determine a mathematical model or set of models based on the given input-output data [7, 8]. The Mathematical models can be represented in the form of mathematical functions of a system by determining the relationship between input and output data at the moment, the past of the system in the future from a set of observed data which is expressed in the family of function parameterization as follows:

$$F = \{\hat{f}(x(t), \theta)\} \tag{1}$$

where \hat{f} is a nonlinear function.

This paper explores an alternate method for determining the mathematical model: the NARX-RBFNN network. This network consists of parameter networks (θ), specifically the RBF networks' weight (w_k), centres (b_k), and width (a_k).

The Radial Basis Function Neural Network (RBFNN) was initially proposed as a feed-forward neural network with a single hidden layer, where radial functions were employed as activation functions [7, 22, 29]. The concept can be mathematically modelled as a system with several inputs and a single output. The mathematical representation of the nonlinear auto-regressive with exogenous input (NARX) model is given by Eq. (10).

$$\hat{y}(t) = \hat{f}(y(t-1), \dots, y(t-n), u(t-1), \dots, u(t-m)) + e(t) \tag{2}$$

where $y(t)$ and $u(t)$ are sampled process output and input at time t , n , and m denote the number of past output and input, is a nonlinear function describing the system behaviours, and $e(t)$ is the approximation error.

The NARX RBFNN architecture used to identify the waste heat boiler system in this study can be shown in Fig. 4.

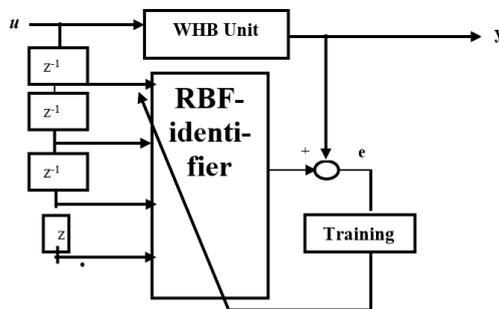


Fig 4. NARX model based on RBF- identifier.

The measurements of the input-output pairs are used to train the network to approximate the dynamic, and the following expression gives the network:

$$\hat{y} = \hat{f}(x) = w_0 + \sum_{k=1}^N w_k h_{a_k, b_k}(x) \tag{3}$$

where $\hat{y} \in R$, $x \in R^{n+m}$, w_k , $h_{a_k, b_k}(x)$, N , w_0 are the RBFNN output, input vector, weight, radial basis function, number of RBF, the bias, respectively.

Several activation functions, such as spline, multi-quadratic, and Gaussian, have been extensively researched. However, the Gaussian type is the most prevalent among them. The Gaussian function [19, 30] is commonly selected as the standard choice for the radial basis function (RBF), and it is defined as follows.

$$h_{a_k, b_k}(x) = \exp\left(-\frac{\|x-b_k\|^2}{2a_k^2}\right) \tag{4}$$

3. RBFNN Algorithm for Identification System

3.1. Training process

Radial Basis Function Neural Network (RBFNN) possess several advantages when addressing challenges related to non-stationary and nonlinear components. The architecture of the RBFNN model consists of three layers: the input layer, the hidden layer, and the output layer [8]. In this study, the RBFNN model structure with a single hidden layer was proposed because it has a simple model structure and computational algorithm and its ability to approximate the non-linear characteristics of the system. The steps of the RBFNN training process consist of:

- 1) Apply Input vector data set \hat{x}_i as training data as input layer.
- 2) Calculation of the output vector of the hidden layer $h_{nk}(x_i)$.
- 3) Compute the output vector of the RBFNN, which is compared with the desired/ measurement output by updating the weight vector to reduce the difference until the error approaches zero [9].

The RBFNN hybrid learning procedure encompasses two distinct phases. The first step involves refining the activation function parameters within the hidden layer associated with unsupervised learning. The second stage entails the modification of the network output weights through a supervised process. As mentioned, the procedure often uses the least squares methodology to approximate the observed or measured output data [19].

The primary objective of the RBFNN identification algorithm is to iteratively adjust the parameters of the RBF-NN model to optimize its performance during the training phase. The parameters can be optimized in the Least Mean Square sense by minimizing a cost function error defined by Ko et al. [10].

$$E = \frac{1}{2} \sum_{t=1}^T e^2(t) \tag{5}$$

The term "error" refers to the discrepancy between the predicted output value of the radial basis function neural network (RBFNN) and the true output data or measured data. For updating the changes of each parameter w_k, b_k, a_k the gradients $\frac{\partial E}{\partial w_k}, \frac{\partial E}{\partial a_k}, \frac{\partial E}{\partial b_k}$ are needed to minimize E . The incremental changes of each coefficient are

$$\Delta w = -\frac{\partial E}{\partial w}, \Delta b = -\frac{\partial E}{\partial b}, \Delta a = -\frac{\partial E}{\partial a} \tag{6}$$

Thus, each coefficient of the network is updated according to the following rule:

$$\underline{w}(t + 1) = \underline{w}(t) + \mu_w \Delta w \tag{7}$$

$$\underline{b}(t + 1) = \underline{b}(t) + \mu_b \Delta b \tag{8}$$

$$\underline{a}(t + 1) = \underline{a}(t) + \mu_a \Delta \underline{a} \quad (9)$$

where μ is the fixed learning rate parameter.

3.2. Validation process

A dataset of 3000 pairs of input and output data has been obtained in real-time from the Plant Historical Data (PHD) software within the Distributed Control System (DCS) TDC-3000. The data was collected at a sampling rate of 1 minute. The training dataset is taken from more than the first 80% of the data or in this case around the first 2500 input output measurement data pairs are taken, and the remaining data is allocated for validation, allowing for the evaluation of the model's performance and generalization capacity. The residual's mean square error (MSE) is a qualitative measure used to assess the goodness of fit. To normalize the MSE, it is divided by the variance of the output signal, as expressed in reference [8].

$$NSRMSE = \frac{1/n \int_{t=1}^n [y(t) - \hat{y}(t)]^2}{1/n \int_{t=1}^n [y(t) - \bar{y}(t)]^2} \quad (10)$$

4. Results Analysis and Performance

4.1. Proposed approach

The amount/quality of steam produced by the boiler is influenced by the temperature, pressure and flow rate of steam produced from combustion in the gas turbine and the water level in the drum. Therefore, various parameters in it must be well controlled, considering its dynamic characteristics that often change to adjust to the existing process load. One important control component is the water level in the High-Pressure Steam Drum (HP drum) which must always be maintained at a certain height. If it is too high, the steam will be wet so that it has the potential to damage the equipment that uses the steam, such as steam turbines, etc. Conversely, if it is too low, the tubes of the boiler in question will become overheated so that the life of the boiler is short. The initial step in designing a control system, especially based on a plant model, is to model the system to determine the characteristics of the system. In this study, a system identification technique was used using the radial basis function neural network approach.

The present study employed a simulation methodology that was substantiated by using empirical measurements, and its findings are not directly linked to the current operational procedures. The primary objective of this measure is to mitigate risks that carry significant financial implications, encompassing security, safety, and expenses. The research methodology under consideration is:

- A comprehensive survey is conducted to acquire a theoretical and empirical foundation, which can be achieved through an examination of relevant literature or by conducting direct field surveys. This literature review aims to gather information on the mechanism and process model of the steam drum waste heat boiler, which serves as the focal point of investigation in this study.
- Real-time data inputs and outputs have been obtained via the Plant Historical Data (PHD) software within the Distributed Control System (DCS) TDC-3000, as depicted in Fig. 5. The network simulation approach is carried out using multi input single output (MISO) with the flow of boiler feed water and product steam as input and the water level in the HP steam drum as output.

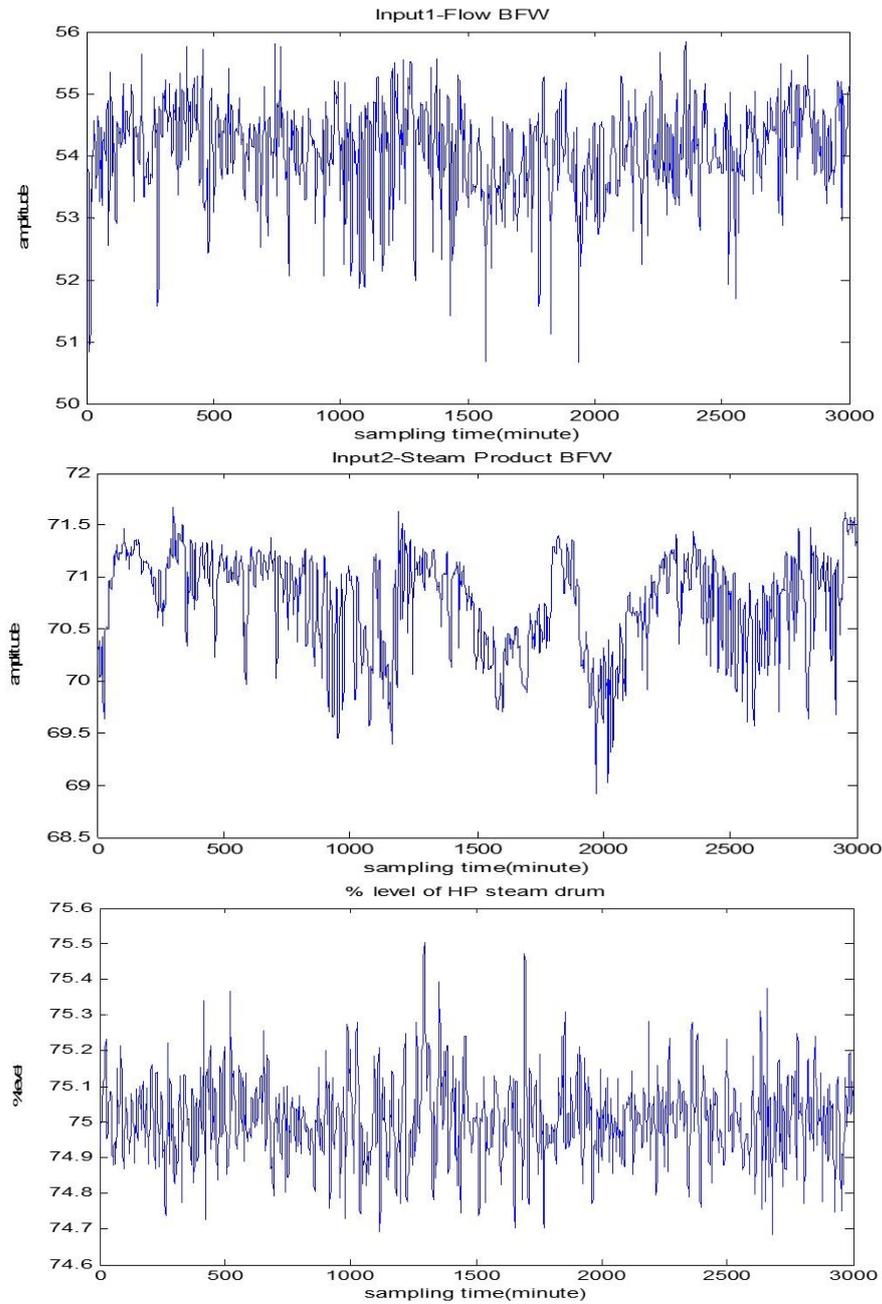


Fig. 5. Input and output data.

- The objective of this study is to establish the RBF identifier as the regressor and model structure by utilizing the following methodology:
 - a. The modelling of the level in a High Pressure (HP) steam drum plant is conducted using a Multi Input Single Output (MISO) approach. This

approach incorporates data on steam flow, Boiler Feed Water (BFW) flow, and the percentage level within the HP steam drum.

- b. Utilizing the process identifier as a parameter estimator is common in the Radial Basis Function Neural Network (RBFNN) architecture.
 - c. No estimated system delay time.
 - d. The unit identification system of the WHB is implemented by a computer approach using MATLAB software.
- Construct a mathematical model of the Waste Heat Boiler (WHB) system using data obtained from both scholarly research and on-site measurement data.

4.2. Determination of the structure of the input-output variable and disturbance

The water level in the HP drum, which will be utilized for the identification process in constructing the modelling system, is influenced by a minimum of two input factors and five measurable disturbance variables, as shown in Table 1.

Table 1. Input-output variable and disturbance.

Input vector	Input [tag number]	Disturbance
$\mu_1(t - 1)$	μ_1 : Flow BFW [FCV.22201]	Pressure BFW : d_1
$\mu_2(t - 1)$	μ_2 : Steam Product Flow[FC.2221]	Temperature BFW: d_2 Pressure HP Drum: d_3 Temperature HP Drum: d_4
	Output [tag number]	Steam Product temperature d_5
$y_m(k - 1),$	y_m : Level Water in HP drum [LC.2223]	
$y_m(k - 2)$		

In this study, it is assumed that no estimation is carried out on the regressor input in the network, so that the selection of estimators/identifiers has been carried out for training to obtain the estimation model in Eq. (11).

$$\hat{y}(t) = \hat{f}(y_m(t - 1), y_m(t - 2), \mu_1(t - 1), \mu_2(t - 1), \theta) \quad (11)$$

4.3. The result of system identification of waste heat boiler plant

A training dataset consisting of 2,500 data points is utilized while acquiring knowledge. The learning rate constant is critical and set at 0.5, which determines how the model estimate changes respect to the estimation error when the model weights are updated. The selection of these parameters is important because it can affect the speed of the network training process and can even cause the process to get stuck or become unstable.

Determining the number of radial basis functions in the network structure is related to the reduction of the model order. This means that it will reduce the number of parameters in the network so that it can affect the network computation time process. In this study, the Final Prediction Error (FPE) criteria [31, 32] will be used in this study, namely minimizing the Eq. (12).

$$J_{FPE}(\hat{f}) = \frac{1+n_d/n_1}{1-n_d/n_2n} \sum_{n=1}^n (\hat{f}(x_n) - y_n)^2 \quad (12)$$

where n_d is the number of parameters in the estimator and d is the input dimension. For this RBFNN, the number of parameters is:

$$n_d = k(d + 2)$$

K = number of radial basis functions in the network. Multiple candidate models can be developed during the identification procedure, as depicted in Table 2.

It is obtained that the best model that minimizes the FPE value is achieved using a Gaussian radial basis function with a count of 9, while the total number of network parameters is 27, which is the parameters of the network respectively w_k, b_k, a_k are weight, dilation and translation. The final prediction error (FPE) value of estimated model is $3,14E-04$ and the addition of the number of RBF nodes ($K > 9$) does not improve the model and even increases its FPE value. It estimates the model-fitting error when we use the model to predict new outputs.

Table 2. The candidate of RBFNN model.

Number of RBF Nodes	NSRMSE	FPE	Time (s)
2	0.6235	0.003	3.55
3	0.5038	0.0017	3.52
4	0.4165	0.0011	3.79
5	0.3526	7.83×10^{-04}	3.67
6	0.3054	5.75×10^{-04}	3.89
7	0.2704	4.43×10^{-04}	3.29
8	0.2448	3.59×10^{-04}	3.33
9	0.2299	3.14×10^{-04}	3.4
10	0.2434	3.49×10^{-04}	3.34

Figure 6 demonstrates that increasing the number of RBFNN nodes decreases the NSRMSE value. However, it is seen that the NSRMSE value exhibits a boost when the number of RBF nodes is set to 10.

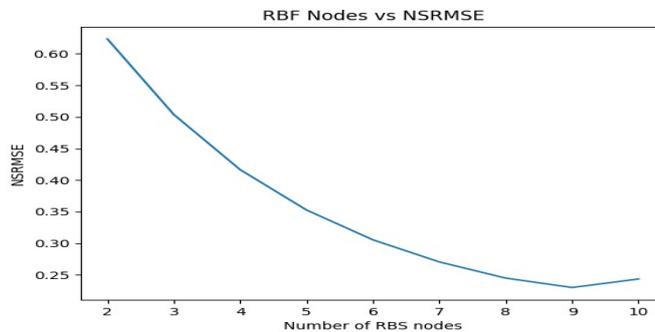
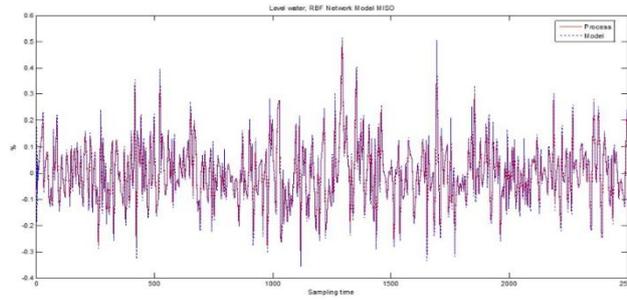
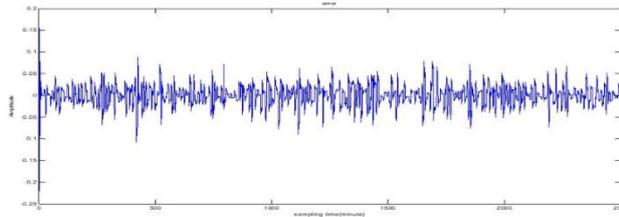


Fig. 6. Numbers of RBF nodes vs NSRMSE.

Figure 7 illustrates the discrepancy between the simulated output of the RBFNN model and the measured output, hence indicating the presence of error. The RBFNN model has effectively detected the true dynamics of the HP steam drum's percentage level. This is proven by the minimum NSRMSE value of 0.2299; the computational time required for this analysis was 3.40 seconds.



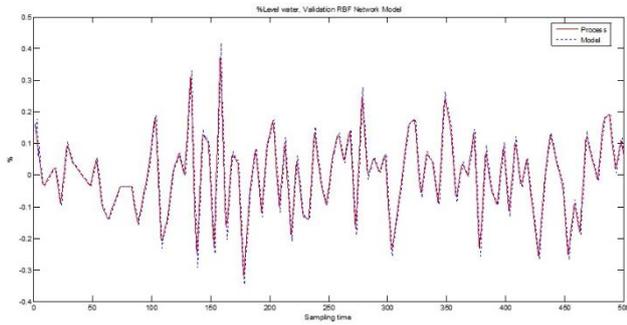
(a)



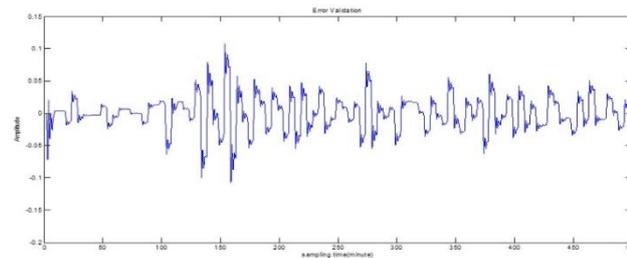
(b)

Fig. 7. (a) The RBFNN model to the measurement output, (b) error.

Following identifying the optimal structure for the Radial Basis Function Neural Network (RBFNN) during the learning phase, the subsequent model validation stage involves employing the remaining 500 measurement data as validation data. Figure 8 displays the outcomes of the validation model and any validation faults.



(a)



(b)

Fig. 8. (a) Validation model and (b) error validation.

The findings indicate that the RBFNN models' output can accurately represent the dynamic nature of real observation measurements. For further research, based on the RBFNN model structure that has been successfully implemented, a control system design will be conducted.

5. Conclusion

The efficacy of the identification method using a Radial Basis Function Neural Network (RBFNN) identifier has been empirically demonstrated. The RBFNN structural model was utilized and examined using measurement data from the waste heat boiler (WHB) facility. After conducting data pre-processing identifying multiple candidate models through programming and simulation using MATLAB, it is observed from the graphical representation that the RBFNN model exhibits a satisfactory match when compared to the actual output measurements. The hybrid learning process is partitioned into 2500 measurement data and 500 data for model validation based on a dataset of 3000 input-output pairs from the WHB unit. The optimal topology for the Radial Basis Function Neural Network (RBFNN) entails using five input vectors as identifiers and incorporating nine RBF nodes within the single hidden layer, resulting in modest Normalized Square Root Mean Square Error (NSRMSE) values of 0.2299. This has the advantage of solving the problem of high dimensions of network inputs of more than 3. This study's findings demonstrate that the RBFNN models' output can accurately represent the dynamic nature of real observation measurements.

Acknowledgement

We would like to thank the Widya Mandala Foundation and the Institute for Research and Community Service, Widya Mandala Catholic University, Surabaya for the opportunity to support this research.

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