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# A New Recurrent Radial Basis Function Network-based Model Predictive Control for a Power Plant Boiler Temperature Control

J. Tavoosi*[a], A. Mohammadzadeh[b]

[a] Department of Electrical Engineering, Ilam University, Ilam, Iran
[b] Department of Electrical Engineering, University of Bonab, Bonab, Iran

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*ABSTRACT*

In this paper, a new radial basis function network-based model predictive control (RBFN-MPC) is presented to control the steam temperature of a power plant boiler. For the first time in this paper the Laguerre polynomials are used to obtain local boiler models based on different load modes. Recursive least square (RLS) method is used as observer of the Laguerre polynomials coefficient. Then a new locally recurrent radial basis function neural network with self-organizing mechanism is used to model these local transfer function and it used to estimate the boiler future behavior. The recurrent RBFN tracks system is dynamic online and updates the model. In this recurrent RBFN, the output of hidden layer nodes at the past moment is used in modelling, So the boiler model behaves exactly like a real boiler. Various uncertainties have been added to the boiler and these uncertainties are immediately recognized by the recurrent RBFN. In the simulation, the proposed method has been compared with traditional MPC (based on boiler mathematical model). Simulation results showed that the recurrent RBFN-based MPC perform better than mathematical model-based MPC. This is due to the neural network's online tracking of boiler dynamics, while in the traditional way the model is always constant. As the amount of uncertainty increases, the difference between our proposed method and existing methods can clearly be observed.

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**NOMENCLATURE**

| | | | |
|---|---|---|---|
| $p$ | Time scale factor | $M(k)$ | Gain matrix in RLS |
| $\Phi_i$ | Laguerre functions | $\mu_i(k)$ | the coefficients of the functions in MPC |
| $Y_m(s)$ | Laplase transform of system's output | $H_i$ | The horizon sample |
| $C_i$ | Output matrices | $u(k)$ | Control input |
| $U(s)$ | Laplase transform of system's input | $\emptyset_i(u)$ | Output of RBF neurons |
| $l_i(s)$ | Terms of Laguerre Ladder network | $w_i$ | Waights in RBFN |
| $\tau_i$ | Time constant of the system | $y_m(k)$ | Output of the model |

## 1. INTRODUCTION

Boilers are used in many industries such as power plants. Power plants use boilers to generate steam for electrical power in steam turbines. The more precise control of the boiler outlet temperature is crucial. If the outlet steam temperature is not properly controlled, the pressure needed to rotate the turbines may not be reached or the efficiency of the boiler and turbine may be reduced. Due to the long history of using boilers in various industries, which reaches more than 150 years, naturally, various methods have been proposed to control outlet temperature. From simple methods such as PID [1] to model free methods such as variable structures adaptive control [2], are each proposed to control the boiler system. The above methods do not require an accurate

*Corresponding Author Institutional Email: *j.tavoosi@ilam.ac.ir* (J. Tavoosi)

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mathematical model of the boiler, but do not perform well in the face of instantaneous changes in the boiler parameters (or uncertainty) as well as different boiler operating conditions. In contrast, various model-based methods for boiler control have been proposed, from coordinated control system [3] to nonlinear model predictive control [4]. Model-based methods can accurately control the boiler; but, if for any reason the boiler dynamics changed or the boiler parameters changed, these methods are not accurate. To solve the above problems, one solution can be the use of computational intelligence. Computational intelligence seems to be a useful tool for precise control of a system [5-7]. Fuzzy logic [8-10] and neural network [11-12] or a combination of the two [13-15] have been used in various papers to identify systems dynamics and control [16-19]. Today, due to the complexity of systems, mathematical model-based approaches alone do not work. Thus, by combining traditional control methods with computational intelligence-based tools, more precise control methods can be proposed [20-21]. Various works have been discussed in the field of boiler and heating system control [22]. In the following we will discuss some of the latest results. Sunil et al. [23] focused on improving the performance of boiler-drum level control over a wide range of operation using the quantitative feedback theory (QFT) approach. A dynamic boiler model has established and validated with values measured from a real power plant [24]. In the mentioned paper, a reheating steam control method is proposed that takes into account changes in heat storage in boiler metals and steam temperature deviations. A fuzzy control has been implemented in the combustion air flowrate of a large boiler in the Tereos group, to maintain the oxygen content in the combustion products within the optimum range [25]. The boiler turbine system is usually subject to the tight input constraint, the strong nonlinearity and the complex disturbance, which makes the control a challenging task. To this end, a disturbance observer based fuzzy model predictive control scheme is proposed for the boiler system in literature [26]. Support vector machin based control by combination the ability of fuzzy logic and learning ability of neural network have been used for boiler control in [27]. Shi [28] has applied a new fuzzy clustering method to boiler temperature control. They used type-2 fuzzy because this tool has high capacity on handling with uncertainty. Uncertainty in the parameter or structure of a system is one of the most challenging issues in control engineering [29]. In the past, the uncertainty of a system was not considered. The reason for this was either insufficient knowledge or negligence. That is why in the past, control systems did not provide the desired and suitable answer. It is clear that most systems that need to be controlled are dynamic and have multiple parameters. Some of these parameters change over time or may change for a moment and then return to the previous state [30]. If the values of the parameters are considered constant in the designed control system, the desired answer will not be obtained in a practical system. Therefore, a control system is successful when it considers as many parametric and systematic changes as possible and has a plan for these changes [31]. Adaptive control systems and robust control systems work well with parametric and structural changes. But these methods require a mathematical and relatively accurate model of the system [32]. In contrast, methods based on computational intelligence (fuzzy logic, neural nets, etc.) have the ability to update themselves and can provide good performance in the face of uncertainties [33-35]. In the following, we will analyze the articles related to applications of neural network in boiler control. A multilayer perceptron neural network model has been developed to envisage the corrosion rate and oxide scale deposition rate in economizer tubes of a coal-fired boiler [36]. The mentioned paper does not talk about temperature control, but parametric sensitivity is well modeled by the neural network. A two layer perceptron neural network has been used to control of a boiler in literature [37]. In the mentioned paper, the inputs of neural network are temperature, pressure and carbon monoxide of the boiler and the outputs are percentage of valve opening for fuel gas supply to the boiler and percentage of valve opening for air supply to the boiler. Unfortunately, load uncertainty are not considered in this article. In literature [38] the perceptron neural network is used to control of a boiler as a two inputs - three outputs system. Inputs are: temperature, pressure and carbon dioxide and outputs are: percentage of valve opening for fuel gas supply and percentage of valve opening to supply air. In the mentioned article, no uncertainty has been applied neither in the parameters nor in the load, also the training and testing error of the neural network is relatively high. A neural network-based controller has been designed for a power boiler to save fuel consumption [39]. In the mentioned article, a proper training and test error has been obtained but any uncertain load has not been applied. A multilayer feed-forward neural network is trained to identify the inverse dynamic model of a boiler system [40]. In the mentioned paper, a perceptron-type three-input-three-output neural network has been used for this purpose, and a completely practical and laboratory work has been done, but unfortunately no uncertainty has been considered for the model.

There is no article that has used the recurrent radial basis neural network to be used in model predictiove control of boiler system, and therefore our proposed method is quite original, but very few articles have used the conventional radial basis neural network to model or control the boiler, some of which are discussed in continue. Kouadri et al. [41] have been able to use the high capability of the radial basis function neural network to model and system identification of the boiler system.

In the mentioned paper, an ordinary (not recurrent) radial base function neural network with training based on genetic algorithm has been used. In literature [42], the ordinary radial base function neural network has been used to inverse control of a boiler system. In the mentioned paper the load uncertainty is not considered and the boiler equations are not clear. An ordinary radial basis function neural network has been performed to identify the boiler system and then use it in the optimal control of the boiler, but not any type of uncertainty (load or parameters) is considered [43]. We have justified by reviewing the above articles that there are shortcomings in this regard. Therefore, in this paper, we proposed a new method to eliminate them. The innovations of our proposed method are as follows:

- In most of the articles, general feedback was used in recurrent RBFNs, while in our proposed method, local feedback was used. In general feedback, the information from the past moment of the last layer is applied as input to the first layer, but in local feedback, the information from the past moment of the output of the neuron itself is used as the input of the same neuron. It should be noted that neural network training with local feedback is far more complex than training with general feedback.
- The second innovation of our method is the use of structural training (Self-Organizing) in regulating the number of neurons in the middle layer of the neural network. In this way, starting from one neuron and due to the complexity of the data, the number of neurons increases, until we achieve the desired minimum error.
- The third innovation is using the Laguerre polynomials to obtain the local boiler models for different boiler load modes.
- The forth innovation is proposed a new structure for MPC based on RBFN. The innovation of this section is using difference formulation for MPC.
- Considering the parameters of a real boiler with real uncertainty is fifth innovation. All numerical and parametric values were measured from a laboratory and practical boiler.

In this paper, the main focus is on the load uncertainty problem. First, the dynamic equations of the boiler system are expressed. Then, the radial basis function neural network prediction model control system is presented. Finally, simulations and conclusions are presented.

## 2. MATHEMATICAL MODELING OF SUPER HEATED STEAM OF POWER PLANT

In this section, first the Laguerre functions are introduced; then, the boiler modeling method is expressed using these functions. Laguerre functions are a complete set of orthogonal functions in Judicial $L_2(0,\infty)$ which are widely used because of the simple and easy expression of its network. These functions come in a series of functions [44]:

$$\Phi_i(t)=\sqrt{2p}\,\frac{e^{pt}}{(i-1)!}\frac{d^{i-1}}{dt^{i-1}}[t^{i-1}.e^{2pt}],\qquad i=1,2,\ldots,\infty \tag{1}$$

are defined where $p$ is a constant called the time scale factor. The laplace transform of Equation (1) is:

$$\Phi_i(t)=l\{\Phi_i(t)\}=\sqrt{2p}\,\frac{(s-p)^{i-1}}{(s+p)^{i})}.\quad i=1,2,\ldots,\infty \tag{2}$$

Every open loop system can be approximated by Laguerre functions as Equation (3):

$$Y_m(s)=\sum_{i=1}^{n}C_i\Phi_i(s)U(s)=\sum_{i=1}^{n}C_i l_i(s) \tag{3}$$

There are several ways to express the Laguerre Ladder network. However, it is desirable for us to express the Laguerre ladder network in the state space so that it can directly predict the outputs of the system. The system state space expression using the Laguerreithmic functions after discretization is as follows [44]:

$$\begin{aligned} &L(k+1)=AL(k)+Bu(k)\\ &y(k)=CL(k)\end{aligned} \tag{4}$$

In Equation (4), the system state vector is $L(k)$ of the order n and u (k) is the input of the system. The matrix A is the lower triangular matrix of NxN. Also B is the matrix of input coefficients of the system (Nx1) whose elements are determined by line-off. This way the amount of computation is greatly reduced. If $T$ is the system sampling period, therefore [44]:

$$\begin{aligned}
&\tau_1=e^{-pT}\\
&\tau_2=T+\frac{2}{P}(e^{-pT}-1)\\
&\tau_3=-Te^{-pT}-\frac{2}{P}(e^{-pT}-1)\\
&\tau_4=\sqrt{2p}\,\frac{(1-\tau_1)}{p}\\
&a=\tau_1\tau_2+\tau_3
\end{aligned} \tag{5}$$

Then the system description matrices for Equation (4) are expressed as follows:

$$\begin{aligned}
&A=\begin{bmatrix}\tau_1 & 0 & & \cdots & 0\\ -\frac{a}{T} & \tau_1 & & \cdots & 0\\ \vdots & & \vdots & \ddots & \vdots\\ \frac{(-1)^{N-1}\tau_2^{n-2}a}{T^{N-1}} & & \cdots & -\frac{a}{T} & \tau_1\end{bmatrix}\\
&B=\left[\tau_1\ \ \left(\frac{-\tau_2}{T}\right)\tau_4\ \ldots\ \left(\frac{-\tau_2}{T}\right)^{N-1}\tau_4\right]^T\\
&\mathrm{L(k)}=[l_1(k)\ \ l_2(k)\ldots l_N(k)]^T\\
&\mathrm{C}=[c_1\ c_2\ldots c_N]
\end{aligned} \tag{6}$$

The vector C, which is the system observer coefficients vector with N + 1 dimensional, is determined by using the recursive least squares (RLS) to express the relationship between the Laguerre model and the desired system.

$$C(k) = C(k-1) + \{M(k)[y(k) - C(k-1)L(k)]\}^T$$
$$M(k) = \frac{P(K-1)L(K)}{\lambda + L^T(K)P(K-1)L(K)} \tag{7}$$
$$P(k) = \frac{1}{\lambda}[P(k-1) - M(k)L^T(k)P(k-1)]$$

where λ is forgetting factor. From Equations (1) to (7), a model of a boiler system can be obtained. As it is clear from the above equations, the obtained model is dynamic and with exponential coefficients and can be a relatively accurate mathematical model of a practical boiler.

## 3. MODEL PREDICTIVE CONTROL

Model predictive control has rules similar to classical prediction control, as both methods use a model to predict the future output of the system. Model predictive control considers the structure of control law as a linear combination of a set of basic functions. Then the weight of the coefficients of the basic functions in the linear combination has to be calculated. The selection of basic functions is also based on the process properties and the desired reference inputs. The structure of the control law can be considered as follows.:

$$u(k+i) = \sum_{n=1}^{N} \mu_n u_{bn}(i) \tag{8}$$

where the $\mu_n$ is the coefficients of the functions with is linear in sequence and specifies the number of base types ($u_{bn}(i)$). The values of the basic functions are instantaneous k+i ($u(k+i)$). The choice of these basic functions depends on the nature of the process and the reference input and generally uses step-slope and parabolic functions. In most cases, however, using two steps to the step and the ramp is sufficient:

$$u(k+i) = \mu_1(k) + \mu_2(k) * i \tag{9}$$

The model predictive control algorithm finds the sum of future control variables in such a way that the output of the process is as close to the reference sequence as possible. The feedback correction sequence is computed by an exponential relation:

$$y_p(k+i) = y_m(k+i) - \lambda^i[y_m(k) - y(k)] \tag{10}$$

where $i = 1,2,\dots,H_i$ are the total number of matching points. $y_p(k+i)$ are the values of the feedback correction sequence at time $k+i$, $y_m(k)$ is also the model outputs (RBFN output) and y(k) are process outputs. $\lambda^i = e^{-\frac{T_s}{T_r}}$ which is $T_s$ the sampling time and $T_r$ the expected response time to the reference sequence .

By combination of Equations (4) and (9), the future output can be obtained.

$$y_m(k+i) = CA^iL(k) + C\left[A^{i-1} + A^{i-2} + \cdots + I\right]B\mu_1(k) + C\left[A^{i-2} + 2A^{i-3} + \cdots + (i-1)I\right]B\mu_2(k) \tag{11}$$

where $y_m(k+i)$ is output of the model at $k+i$.

MPC is a control strategy that explicitly uses the process model to predict the future behavior of the process output in a finite horizon, and the control effort is achieved by minimizing the interaction between the predicted output of the model and the reference sequence at a given time horizon. The predictive control law is generally computed by minimizing the axial scaling:

$$J = \sum_{i=H_1}^{H_2} [y_p(k+i) + e(k+i) - y_r(k+i)]^2 \tag{12}$$

In relation to the control effort, only two coefficients of the basic functions, $\mu_1(k)$ and $\mu_2(k)$, are uncertain. In order to determine these unknown parameters, we rewrite the above relations [44]:

$$J = [y_p(k+H_1) + e(k+H_1) - y_r(k+H_1)]^2 + [y_p(k+H_2) + e(k+H_2) - y_r(k+H_2)]^2 \tag{13}$$

We will have the following relationship by replacing the reference sequence and predicting the process output.

$$[X_1(k) + M_{11}\mu_1(k) + M_{12}\mu_2(k)]^2 + [X_2(k) + M_{12}\mu_1(k) + M_{22}\mu_2(k)]^2 \tag{14}$$

In this regard:

$$\begin{aligned} X_1(k) &= CA^{H_1}L(k) + e(k+H_1) - y_r(k+H_1) \\ X_2(k) &= CA^{H_2}L(k) + e(k+H_2) - y_r(k+H_2) \\ M_{11} &= C(A^{H_1-1} + A^{H_1-2} + \cdots + I)B \\ M_{12} &= C(A^{H_1-2} + 2A^{H_1-3} + \cdots + (H_1-1)I)B \\ M_{21} &= C(A^{H_2-1} + A^{H_2-2} + \cdots + I)B \\ M_{22} &= C(A^{H_2-2} + 2A^{H_2-3} + \cdots + (H_2-1)I)B \end{aligned} \tag{15}$$

From Equation (15), all required coefficient and variables in Equation (14) are calculated. Now, by deriving the relation to the unknown parameters, we obtain:

$$\mu_1(k) = S_y y(k) + S_L L(K) + S_W W(k) \tag{16}$$

In this regard

$$\begin{aligned} S_y &= Q(Q_3M_{12} - Q_2M_{11})(1-\alpha^{H_1}) + Q(Q_3M_{22} - Q_2M_{21})(1-\alpha^{H_2}) \\ S_L &= Q(Q_3M_{12} - Q_2M_{11})C(A^{H_1} - I) + Q(Q_3M_{22} - Q_2M_{21})C(A^{H_2} - I) \\ S_w &= -S_y \\ Q_1 &= M_{11}^2 + M_{21}^2 \\ Q_2 &= M_{12}^2 + M_{22}^2 \\ Q_3 &= M_{11}M_{12} + M_{21}M_{22} \\ Q &= 1/(Q_1Q_2 - Q_3^2) \end{aligned} \tag{17}$$

Using the above relationships, we can write the following relation for control effort:

$$u(k)= \mu_1(k) = S_y y(k)+S_L L(k) + S_w w(k) \quad (18)$$

Note that only the parameter ($\mu_1(k)$) can be specified if (Q) exists, so in selecting the free controller parameters, $H_1$ and $H_2$, care should be taken to select the matrix (Q) would have existed. There are three main factors that can affect the output temperature of the boiler: load, steam flow and boiler internal steam temperature. The effect of load is more than others. Each change in load leads to a different behavior from the boiler. In such a way that for each load, the boiler will have a different conversion function. Other factors such as: the temperature of the injected water, the temperature of the injected steam into the super heater, the pollution on the walls, the sediment in the steam pipes, etc. can all be of uncertainty sources. Five local transfer functions with different load percentages are summarized in Table 1. For five different load modes, five transfer functions can be obtained.

Thus, all five transfer function can be modeling in one model by using recurrent RBFN. The prposed recurrent RBFN is shown in Figure 1.

In the middle layer containing RBF neurons, the neuron-governing relationship is as follows:

$$\emptyset_i(u) = exp\left(-\frac{\|u-c_i\|^2}{\sigma_i^2}\right), \qquad i = 1, \dots, m \quad (19)$$

**TABLE 1.** Five local transfer function

| Load % | Equivalent Transfer Function |
|---|---|
| 30 | $\frac{-11.24}{1+124.4s}e^{-115s}$ |
| 40 | $\frac{-10.16}{1+91.8s}e^{-101s}$ |
| 60 | $\frac{-9.55}{1+80.7s}e^{-94.5s}$ |
| 80 | $\frac{-7.61}{1+78.1s}e^{-82.1s}$ |
| 100 | $\frac{-4.59}{1+53.83s}e^{-58.5s}$ |

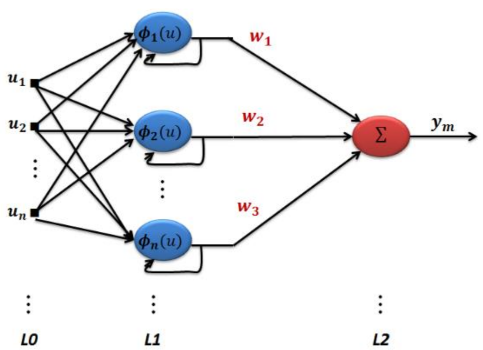


**Figure 1.** The proposed recurrent RBFN

where $\sigma_i \in R$ the width of the neuron is, $c_i = [c_{1i}, c_{2i}, \dots, c_{ni}]^T$ is the center vector of the neuron and $u = [u_1, u_2, \dots, u_n, \emptyset(u(k-1))]^T$ is the network input. In the last layer, the output is calculated.

$$y = \sum_{i=1}^{m} w_i \, \emptyset_i(u) \quad (20)$$

Here the output from the given weight of the nonlinear bases is $\emptyset_i(u)$ which it must be orthogonal. In the structural training (Self-Organaizing) of the radial basis function neural network, there is initially only one neuron. Upon entering the first data, the Euclidean distance of this data from the center of the neuron is calculated. If this data belonged to an existing neuron then the next data is coming, but if it did not belong, a new neuron will be created for this data. This process of adding neurons continues until the end of training and applying the latest data. For more details of RBFN training one can refer to literature [7].

The overall goal is to reduce the error between the actual system and the model.

$$e(k+i) = y(k) - y_m(k) \quad (21)$$

The structure of the proposed control system is shown in Figure 2.

The process is as follows: first, all transfer functions (here are 5 functions) are modeled by a single recurrent RBF neural network (green block in Figure 2), and so this neural network simultaneously includes all models. Therefore, if the boiler load changes, the recurrent RBF neural network immediately generates the appropriate signal and assists the controller. The boiler block (red block in Figure 2) contains the transfer functions in Table 1. The feedback correction block (orange block in Figure 2) performs the calculations for Equation (10). Finally, the optimization algorithm (blue block in Figure 2) performs the calculations for Equation (18).

## 4. SIMULATIONS

In this section, simulation of the boiler with the proposed control method in MATLAB software is discussed. The parameters of boiler are shown in Table 2.

In continue, the performance of the proposed control system, i.e. the neural network-based MPC, as well as the

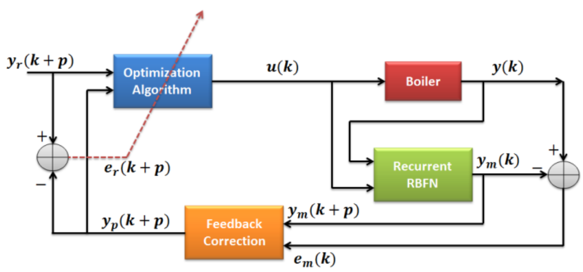


**Figure 2.** The structure of the proposed control system

**TABLE 2.** System parameter values

| | |
|---|---|
| Nominal power | 100 MW |
| Vapor flow rate | 120 $kg/sec$ |
| Steam pressure | 120 $kg/cm^2$ |
| Steam temperature | 510 °C |
| Drum size | 30 $m^3$ |
| Water mass | 30000 $kg$ |
| Steam mass under pressure | 1500 $kg$ |
| Inlet water temperature | 37 °C |
| Fuel flow rate | 12 $kg/sec$ |

performance of the conventional MPC, are compared. It is expected that in our proposed method, the existence of a RBF neural network will lead to a more precise handling of the uncertainty and follow the changes well, and it should perform better than the traditional method. Figure 3 shows the boiler temperature control by recurrent RBFN-based MPC and traditional MPC without load uncertainty.

For greater clarity, part of Figure 3 is enlarged and shown in Figure 4.

According to Figures 3 and 4, the complete superiority of the proposed MPC method based on RBFN over the traditional MPC is clear. As can be clearly seen in Figure 4, in the traditional MPC method the boiler temperature range is from 870 to 923, while in the RBFN-based method this range is from 890 to 905. In other words, the RBFN softens some of the controller switching. In continue, the performance of both traditional MPC and RBFN-based MPC are challenged with uncertainty in load. It is assumed that the boiler load will change randomly by $\pm 15\%$. Figure 5 shows the boiler temperature control by recurrent RBFN-based MPC and traditional MPC $\pm 15\%$ in load uncertainty.

For greater clarity, part of Figure 5 is enlarged and shown in Figure 6.

In order to evaluate the performance of the controllers by increasing the load uncertainty, the uncertainty value of the boiler load is increased randomly to $\pm 25\%$. Figure 7 shows the boiler temperature control by recurrent RBFN-based MPC and traditional MPC $\pm 25\%$ in load parameter uncertainty.

For greater clarity, part of Figure 7 is enlarged and shown in Figure 8.

Finally, increase the uncertainty on the boiler load to $\pm 50\%$ and you will see the result in Figure 9.

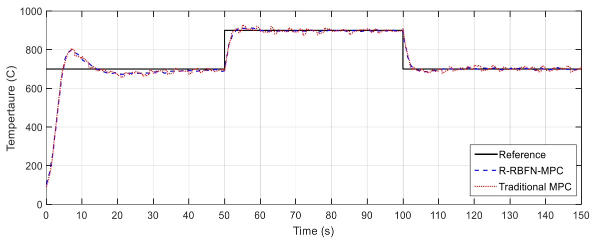


**Figure 3.** Simulation results of recurrent RBFN-MPC and traditional MPC for temperature boiler control without any uncertainty

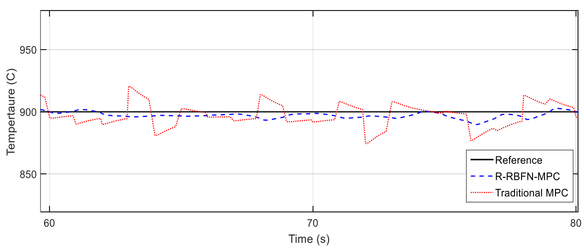


**Figure 4.** Zoom in on part of Figure 3

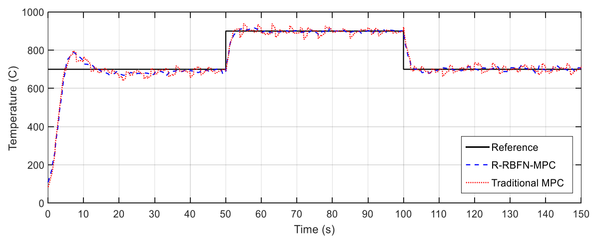


**Figure 5.** Simulation results of recurrent RBFN-MPC and traditional MPC for temperature boiler control with $\pm 15\%$ in load uncertainty

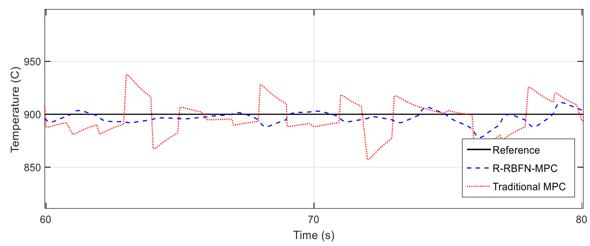


**Figure 6.** Zoom in on part of the Figure 5

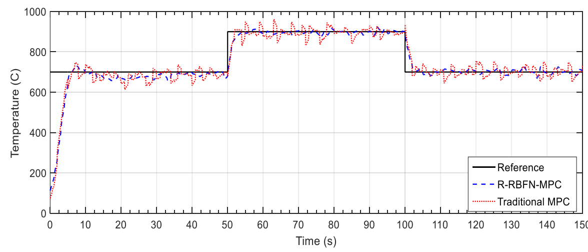


**Figure 7.** Simulation results of recurrent RBFN-MPC and traditional MPC for temperature boiler control with $\pm 25\%$ in load uncertainty

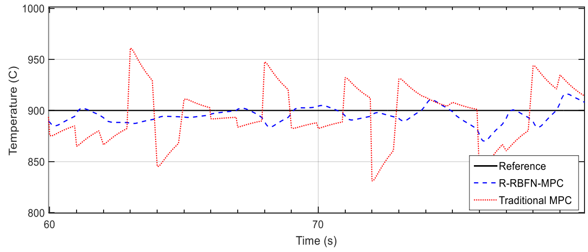


**Figure 8.** Zoom in on part of the Figure 7

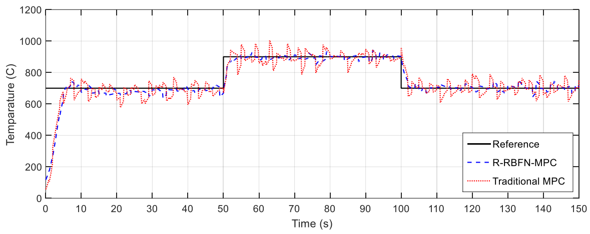


**Figure 9.** Simulation results of recurrent RBFN-MPC and traditional MPC for temperature boiler control with ±50% in load uncertainty

For greater clarity, part of Figure 9 is enlarged and shown in Figure 10.

From Figures 3 to 10 can be conclude that if the more uncertainty of the load, the greater the superiority of the recurrent RBFN-MPC over the traditional MPC. When the uncertainty reaches ±50%, the traditional MPC is practically useless, because the teprarature changes from 800 ℃ to 1000 ℃ instead of being fixed at 900 ℃. See Table 3 for further comparison of the proposed method with some of the existing works. In this table, the measurement criterion is the root mean square tracking error (RMSE) [20].

As shown in Table 3, the use of computational intelligence (neural network, fuzzy logic, etc.) as a complement to a control system can be very useful. Boiler is a highly nonlinear system with uncertain parameters. As shown in the simulation results, for a real boiler can not be considered a fixed model with fixed parameters. It seems that the traditional MPC method behaves like this, but by combining it with computational intelligence, changes can be tracked immediately. This becomes especially critical when the rate of change is

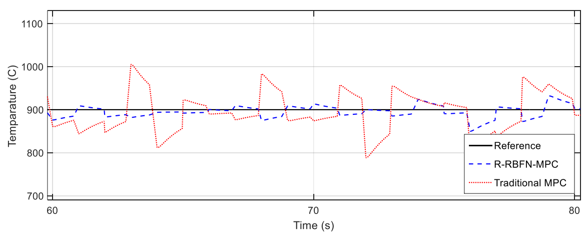


**Figure 10.** Zoom in on part of Figure 9

**TABLE 3.** Comparison of the proposed method with some of the existing works

| | No. load | ±15% uncertainty | ±25% uncertainty | ±50% uncertainty |
|---|---|---|---|---|
| Method of [23] | 2.271 | 2.441 | 3.318 | 4.776 |
| Method of [25] | 1.421 | 1.948 | 2.559 | 2.985 |
| Method of [37] | 1.258 | 1.882 | 2.052 | 2.891 |
| Method of [42] | 1.326 | 1.691 | 2.174 | 2.221 |
| Alone MPC | 1.545 | 1.962 | 2.498 | 2.993 |
| Our proposed method | 0.855 | 1.121 | 1.573 | 1.989 |

high and traditional methods do not respond well at all. Neural networks, if properly trained with appropriate and useful data, can well approximate a function and estimate future moments, and this is very useful in controlling systems.

## 5. CONCLUSION

In this paper, a combination of computational intelligence with model predictive control was used to control the power plant boiler. In this method, a self-organazing recurrent radial base function neural network was used for online modeling of the boiler. First, several local transfer functions of the boiler were created using the Laguerre polynomials method, then the recurrent RBF neural network was used to approximate these models. Laguerre polynomial coefficients are calculated and updated by the recursive least squares algorithm (RLS). The recurrent RBFN can estimate future moments for the model predictive method and use it to accurately control the boiler. As observed in the simulation results, when we have uncertainty in the load, the neural network-based model predictive control works better than the traditional model predictive control, especially when the uncertainty is high. All numerical values of the parameters and their mathematical relations are based on a real boiler system. Therefore, the proposed method in this paper has the capability to implement hardware and practice.

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## Persian Abstract


**چکیده**

در این مقاله، مدل جدید کنترل پیش‌بینی مبتنی بر شبکه تابع پایه شعاعی (RBFN-MPC) برای کنترل دمای دیگ بخار نیروگاهی ارائه شده است. برای اولین بار در این مقاله از چند جمله‌ای لاگر برای بدست آوردن مدل‌های محلی دیگ بخار بر اساس حالت‌های مختلف بار استفاده شده است. از روش حداقل مربعات بازگشتی (RLS) جهت بروزرسانی ضرایب چند جمله‌ای لاگر استفاده می‌شود. سپس برای مدل‌سازی محلی از شبکه عصبی تابع پایه شعاعی بازگشتی با مکانیزم خودتنظیمی استفاده شده و از آن برای تخمین رفتار آینده دیگ بخار استفاده می‌شود. در این RBFN بازگشتی، از خروجی گره‌های لایه پنهان در لحظه گذشته در مدل‌سازی استفاده می‌شود، بنابراین مدل دیگ بخار دقیقاً مانند یک دیگ بخار واقعی رفتار می‌کند. عدم قطعیت‌های مختلفی به دیگ بخار اضافه شده و این عدم قطعیت‌ها بلافاصله توسط RBFN بازگشتی شناسایی می‌شوند. در شبیه‌سازی، روش پیشنهادی با MPC سنتی (بر اساس مدل ریاضی دیگ بخار) مقایسه شده است. نتایج شبیه‌سازی نشان می‌دهد که MPC مبتنی بر RBFN بازگشتی عملکرد بهتری نسبت به MPC مبتنی بر مدل ریاضی دارد. این به دلیل ردیابی آنلاین دینامیک دیگ بخار توسط شبکه عصبی است، در حالی که به روش سنتی، مدل همیشه ثابت است. با افزایش میزان عدم اطمینان، تفاوت بین روش پیشنهادی ما و روش‌های موجود بیشتر مشخص می‌شود.