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Cascade control of superheated steam temperature with neuro-PID controller

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A B S T R A C T

In this paper, an improved cascade control methodology for superheated processes is developed, in which the primary PID controller is implemented by neural networks trained by minimizing error entropy criterion. The entropy of the tracking error can be estimated recursively by utilizing receding horizon window technique. The measurable disturbances in superheated processes are input to the neuro-PID controller besides the sequences of tracking error in outer loop control system, hence, feedback control is combined with feedforward control in the proposed neuro-PID controller. The convergent condition of the neural networks is analyzed. The implementation procedures of the proposed cascade control approach are summarized. Compared with the neuro-PID controller using minimizing squared error criterion, the proposed neuro-PID controller using minimizing error entropy criterion may decrease fluctuations of the superheated steam temperature. A simulation example shows the advantages of the proposed method.

1. Introduction

Superheated steam temperature plays an important role in the security and economy of power plants. Control of superheated steam temperature is not only economically essential in terms of improving lifetime and efficiency, but also technically challenging because of the complex superheater process characterized by nonlinearity, uncertainty and load disturbance.

A lot of efforts have been made to develop advanced control algorithms for controlling superheated steam temperatures in power plants. Generic model control (GMC) algorithm was developed to control steam temperature and compared with a state feedback controller in [1], however, both control algorithms cannot deal with variant operating condition adaptively.

Predictive control theory has been spread in process industry [2–9]. Generalized predictive control strategy has been applied to control the steam temperature in a 265 MW unit [2]. Dynamic Matrix Control algorithm was implemented in a simulator to control the superheated and reheated steam temperature respectively in [3]. A neuro-fuzzy generalized predictive controller was proposed to regulate superheated steam temperature of a 200 MW power plant [4]. A nonlinear predictive controller based on neural networks was presented to control the superheated steam temperature, reheated steam temperature and pressure in a power plant [5]. Though some linear predictive controllers have been applied by the field, however, the nonlinear predictive control law is encountering some challenges to improve its efficiency and robustness [6–9].

In addition, some other adaptive control algorithms were also developed for regulating steam temperature in power plants. Based on the estimated parameters, an adaptive control system was applied to control the superheated and reheated steam temperature of a 375 MW power plant [10]. An adaptive optimal control method was developed for steam temperature control of a once-through coal fired boiler in [11].

Intelligent control strategies were also applied to control superheated steam temperatures. Fuzzy logic control algorithm was used to control the steam temperature in [3]. An effective neuro-fuzzy model of the de-superheating process was developed, the genetic algorithm based PI controller was proposed to regulate steam temperature of four 325 MW power plants in [4,12]. Neural networks were applied to control temperature in a thermal power plant with once-through boilers [5,13].

Cascade controllers are still most popular and commonly available in steam temperature control systems, because cascade control system has three advantages [14]: (1) reject disturbances arising in the inner loop; (2) improve the speed and accuracy of system response and (3) reduce the effect of parameter variations in the inner loop. In order to improve control performance of superheated steam temperature control systems in power plants, the conventional primary PID controller can be replaced by other advanced controller, moreover, feedforward controller can also be combined with cascade controller. Hence, some improved cascade control strategies have been designed to regulate superheated steam temperature of power plants [2–4,15–17]. A PT_x model which adapts with operating point was incorporated with a

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cascade control strategy in order to compensate high-order and load-dependent dynamics of the superheater. In addition, both generalized predictive controller and fuzzy controller acted as the primary controller in the superheated steam temperature cascade control system in [2]. Combining feed-forward control and cascade control algorithm, a three-element controller was presented to control superheated steam temperature in [15], in which the feedforward controller compensates for load changes. In [16], an LQ self-tuning controller minimizing a multi-step quadratic control performance index was applied to replace the primary PI controller in the cascade control structure for superheated steam temperature control in a 200 MW coal-fueled power plant. The MUSMAR predictive adaptive controller was served as primary controller in the cascade control scheme for regulating superheated steam temperature in an industrial boiler [17]. A neuro-fuzzy generalized predictive controller was proposed to be primary controller in the cascade control system for regulating superheated steam temperature of a 200 MW power plant [4].

In this study, cascade control structure is still used to control superheated steam temperature due to its advantages. However, the conventional cascade PID system may be unsatisfactory when dealing with stochastic disturbances and variable operation conditions. Consequently, it calls for an advanced approach to control superheated steam temperature under the framework of cascade control and stochastic control.

The fluctuations of superheated steam temperature under different control schemes are shown in Fig. 1. y_{max} is the allowable limit of superheated steam temperature according to the thermal stress of the plant. Compared with the control scheme B, the control scheme A can reduce the fluctuations of the superheated steam temperature. The shape of the probability density function of the temperature under scheme A is narrower and sharper than that under the scheme B. As a result, the set-point of temperature y_{Asp} can be set to a higher value because the controlled superheated steam temperature does not violate the upper bound y_{max} under the control scheme A. Hence, the scheme A not only prevents from mechanical stress causing micro-cracks but also provides high efficiency of the turbine.

Disturbances in the superheater process, such as steam mass flow, flue gas and attemporator water mass flow, can cause fluctuations of superheated steam temperature besides variations of load. Not only these disturbances are not necessarily Gaussian, but also the dynamics of the real superheated process is nonlinear, hence, the entropy of tracking error is used to characterize the performance of the closed-loop control systems rather than variance of tracking error.

Following the advancement in dynamic stochastic distribution controller [18–24] and neuro-PID controller [13,25,26], a neural networks assisted PID controller using minimizing error entropy (MEE) criterion is presented to act as a primary controller in superheated steam temperature cascade control systems. The entropy of tracking error is obtained by receding horizon technique. The inputs of the neuro-PID controller include not only the sequences of tracking error but also the measurable disturbances in superheated processes so as to deal with disturbances quickly. The proposed neuro-PID controller can reduce the dispersion of tracking error rather than the existed neuro-PID controller under minimizing squared error (MSE) criterion [13,25–27]. In general, the proposed neuro-PID controller not only overcomes the tedious tuning for the PID controller, but also makes the control system adaptive and robust. Similarly, predictive controller also uses the "receding horizon" idea, the optimal controller inputs can be solved under MSE criterion. Although predictive controller is able to take into account of constraints, however, it is still necessary to do further research on nonlinear predictive control algorithm to improve its efficiency and robustness [6–9].

The rest of this paper is organized as follows: Section 2 describes the superheater process and introduces the basic structure of the proposed cascade controller for regulating superheated steam temperature of power plants. Section 3 presents the primary neuro PID controller using MEE criterion, and analyzes the convergent condition of the neuro-PID controller. Section 4 addresses the problems related to the implementation of the proposed control scheme. Section 5 verifies the efficiency and feasibility of the proposed approach to regulate superheated steam temperature by comparing with a cascade control system whose primary controller is a neuro-PID controller under MSE criterion. Section 6 concludes this paper.

2. Plant description and control scheme

The boiler process usually includes several steam superheating processes shown in Fig. 2: low temperature superheater, platen superheater and high temperature superheater. Each of these processes serves as an energy transferring system, in which energy is transferred from the flue gas to the steam. Each superheater is equipped with an attemperator, water is injected at the inlet of attemperator for control of the steam outlet temperature.

The steam is generated from the boiler drum and passes through the low-temperature superheater before entering the platen superheater where it receives a spray water injection to control the temperature of steam. Similarly, there is a spray water

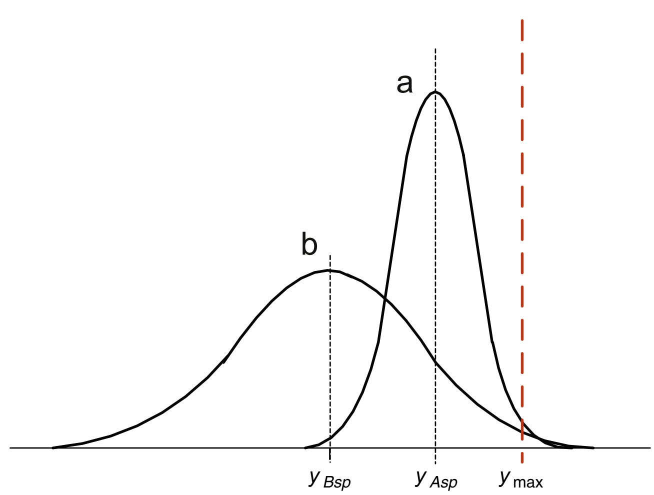

Fig. 1. Control fluctuations of superheated steam temperature.

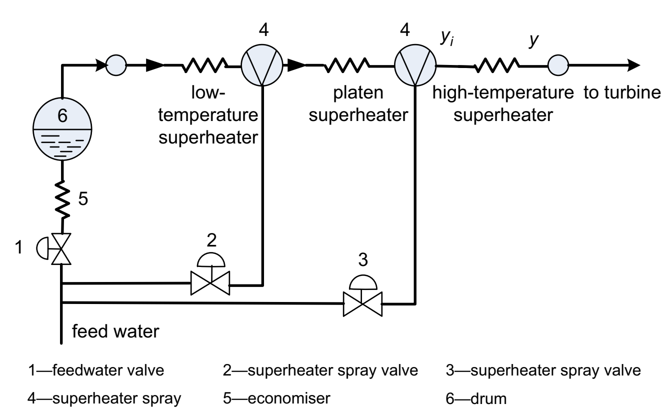

Fig. 2. Superheater process.

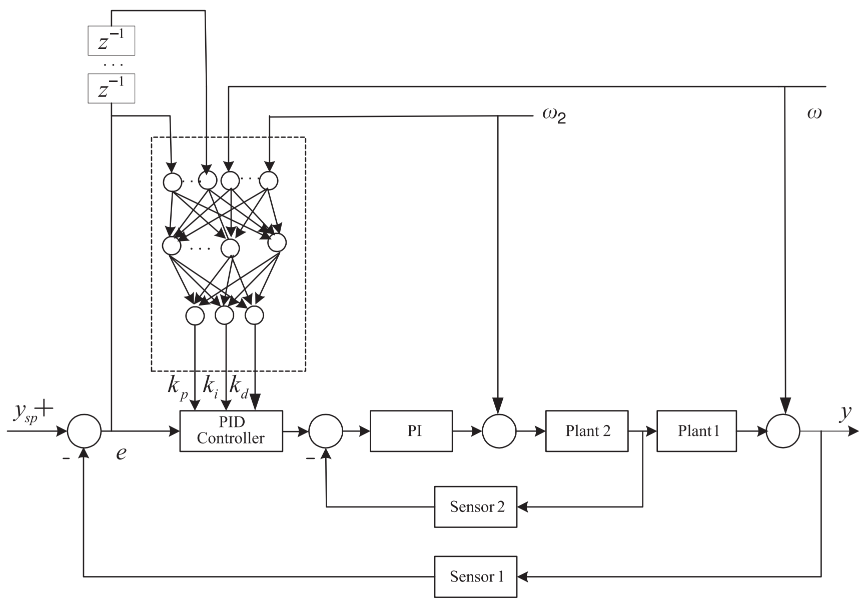

Fig. 3. Improved cascade control system.

injection to control the temperature of steam before the high-temperature superheater. The superheated steam is then extracted by the turbine and accordingly load changes are introduced.

The general objective of the control loop is to maintain a specified temperature level at the outlet of high-temperature superheater. The measure of intermediate steam temperature after spray water injection and before the high temperature superheater is available. The manipulated variable is the position of spray water valves which influences the flow of spray water.

In this paper, we focus on the regulation of secondary spray attemperator. The proposed neural networks assisted cascade control system is shown in Fig. 3. Plant1 is the inertia plant constituted by high temperature superheater, Plant2 the leading plant which contains the attemperator and water/steam mixing in inner loop. ω_2 stands for the disturbance that entered the inner loop while ω is the disturbance in the outer loop. The primary parameter y is the superheated steam temperature, y_{sp} is the set-point of superheated steam temperature and $e = y_{sp} - y$ the tracking error.

The primary controller is performed such that the superheated steam temperature y approaches to its set point y_{sp}. The proposed primary controller is a neuro-PID controller whose parameters k_p, k_i, and k_d are optimized by a back-propagation (BP) algorithm under MEE criterion. The inputs of neural PID controller include the sequences of tracking error in the outer loop and some measurable disturbances.

The secondary controller roughly regulates intermediate steam temperature y_i which embodies varying trend of superheated steam temperature in advance. Thus, the secondary controller G_{c2} in the inner loop is selected to be a proportional controller which should be tuned such that the secondary control loop is much faster than the primary loop.

3. Neuro-PID controller

PID controller is popular in distributed control systems of power plants [28]; however, it is tedious to tune PID parameter. In addition, it calls for adaptive controller to reject disturbances and fit in with the variant operation conditions. The contribution of this paper is to design a neuro-PID controller to serve as a primary controller in cascade control systems. Multilayer perceptron is one of the well-developed neural networks with back-propagation algorithm. The proposed neuro-PID controller shown in Fig. 3 still uses the basic structure of the three layer perceptron. However, the weights of neural networks are trained using gradient algorithm to minimize the entropy of the tracking error rather than the squared error in the outer loop.

3.1. Performance index

Since the disturbances in steam temperature control systems are not necessarily Gaussian and the dynamics of real superheated process is nonlinear, entropy is introduced to measure the dispersion of the steam temperature. Entropy is a more general measure of uncertainty for arbitrary random variables [20]. Thus, the entropy of tracking error is used to construct the performance index of the outer closed-loop control systems. Ideally, the shape of the probability density function of the tracking error should be made as narrow and sharp as possible, it can be characterized by a small entropy of tracking error [21]. For this purpose, the performance index of the closed-loop which is used to update the weights of the neuro-PID controller is selected as quadratic Renyi entropy of tracking error.

$$J = -\log \int_{-\infty}^{\infty} \gamma^2(e)de \tag{1}$$

As Renyi's quadratic entropy is a monotonic function of $V(e) = \int_{-\infty}^{\infty} \gamma^2(e)de$ called information potential in [29], the primary control input can be solved by minimizing the negative information potential of tracking error instead of the Renyi's quadratic entropy so as to decrease computational complexity.

In order to calculate the above performance index, it is necessary to estimate the probability density function (PDF) of closed-loop tracking error $\gamma_{e_k}(x)$ from error sequences e_k using the Guassian kernel functions $\kappa(x,\sigma^2) = 1/(\sqrt{2\pi}\sigma)\exp(-x^2/2\sigma^2)$ recursively:

$$\hat{\gamma}_{e_k}(x) = (1-\lambda)\hat{\gamma}_{e_{k-1}}(x) + \lambda\kappa(x-e_k,\sigma^2) \tag{2}$$

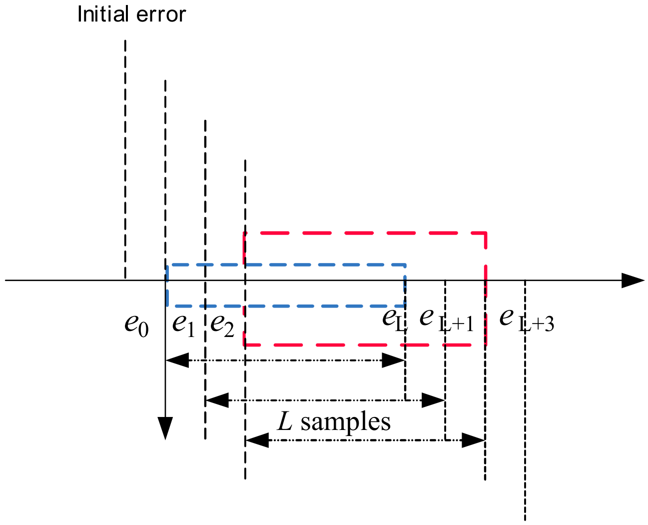

Fig. 4. Estimation of V_k by receding horizon window technique.

where $0 \le \lambda < 1$ is the forgetting factor. Consequently the information potential of tracking error also can be approximated recursively:

$$V_k(e) \cong (1-\lambda)V_{k-1}(e) + \frac{\lambda}{L}\sum_{i=k-L}^{k-1}\kappa(e(i)-e(k),2\sigma^2) \tag{3}$$

where L is the width of the receding horizon window which should be selected to contain the dynamic characteristics of the plant. The information potential of the tracking error obtained by receding horizon technique is shown in Fig. 4.

3.2. *Neuro-PID controller auto-tuning algorithm*

As far as the primary neuro-PID controller concerned, the input nodes denoted by $O_1^{(1)}, O_2^{(1)} \cdots O_3^{(Q)}$ are the tracking error $e_k, e_{k-1},\ldots,e_{k-\bar{n}}$ besides the measurable disturbances ω and ω_2. The number of the hidden nodes is selected experimentally.

The primary controller produces the following control input

$$u_k = u_{k-1} + k_p(e_k - e_{k-1}) + k_i e_k + k_d(e_k - 2e_{k-1} + e_{k-2}) \tag{4}$$

(1) Hidden layer
The input and output of the hidden layer are

$$net_p^{(2)}(k) = \sum_{q=0}^{Q} w_{pq}^{(2)} O_q^{(1)}(k), \quad q = 0,1,\ldots,Q \tag{5}$$

and

$$O_p^{(2)}(k) = f(net_p^{(2)}(k)), \quad p = 0,1,\ldots,P \tag{6}$$

where P and Q are the number of nodes in hidden and input layer respectively.

(2) Output layer
The input and the output of the output layer are

$$net_l^{(3)}(k) = \sum_{p=0}^{P} w_{lp}^{(3)} O_p^{(2)}(k), \quad l = 1, 2, 3 \tag{7}$$

and

$$O_l^{(3)}(k) = g(net_l^{(3)}(k)), \quad l = 1, 2, 3 \tag{8}$$

where the output nodes denoted by $O_1^{(3)}$, $O_2^{(3)}$ and $O_3^{(3)}$ are k_p, k_i and k_d respectively. The activation functions are $f(x) = (e^x - e^{-x})/(e^x + e^{-x})$ and $g(x) = e^x/(e^x + e^{-x})$. w_{lp} and w_{pq} are the corresponding weights updated using steepest descent approach. Following the neural PID controller presented in [23], an improved training algorithm is presented based on recursive estimation of the information potential of tracking error.

(3) Update the weights between the hidden and output layer, w_{lp}

$$w_{lp}(k+1) = w_{lp}(k) + \eta\frac{\partial V_k}{\partial w_{lp}} \tag{9}$$

$$\frac{\partial V_k(e)}{\partial w_{lp}} = -\frac{\lambda}{2L\sigma^2}\sum_{i=k-L}^{k-1}(e(i)-e(k))\kappa(e(i)-e(k),2\sigma^2) \times\left(\frac{\partial e(i)}{\partial w_{lp}} - \frac{\partial e(k)}{\partial w_{lp}}\right) + (1-\lambda)\frac{\partial V_{k-1}(e)}{\partial w_{lp}} \tag{10}$$

$$\frac{\partial e(k)}{\partial w_{lp}} = -\frac{\partial y(k)}{\partial w_{lp}} = -\frac{\partial y(k)}{\partial u(k)}\cdot\frac{\partial u(k)}{\partial O_l^{(3)}}\cdot\frac{\partial O_l^{(3)}}{\partial net_l^{(3)}}\cdot\frac{\partial net_l^{(3)}}{\partial w_{lp}} \tag{11}$$

where η is the learning factor. The Jacobian information $\partial y(k)/\partial u(k)$ can be replaced by $\mathrm{sgn}(\partial y(k)/\partial u(k))$ or calculated by model prediction algorithm of the plant.

$$\begin{aligned}
&\frac{\partial O_l^{(3)}}{\partial net_l^{(3)}} = g'(net_l^{(3)}(k)) \\
&\frac{\partial net_l^{(3)}}{\partial w_{lp}} = O_p^{(2)} \\
&\frac{\partial u(k)}{\partial O_l^{(3)}} = \begin{cases} e(k)-e(k-1), & l=1 \\ e(k), & l=2 \\ e(k)-2e(k-1)+e(k-2), & l=3 \end{cases}
\end{aligned} \tag{12}$$

Hence, the weights between hidden layer and output layer can be calculated from Eqs. (9)–(12).

(4) Update the weights between the input and hidden layer, w_{pq}

$$w_{pq}(k+1) = w_{pq}(k) + \eta\frac{\partial V_k}{\partial w_{pq}} \tag{13}$$

$$\frac{\partial V_k(e)}{\partial w_{pq}} = -\frac{\lambda}{2L\sigma^2}\sum_{i=k-L}^{k-1}(e(i)-e(k))\kappa(e(i)-e(k),2\sigma^2)\left(\frac{\partial e(i)}{\partial w_{pq}} - \frac{\partial e(k)}{\partial w_{pq}}\right) + (1-\lambda)\frac{\partial V_{k-1}(e)}{\partial w_{pq}} \tag{14}$$

where

$$\frac{\partial e(k)}{\partial w_{pq}} = -\frac{\partial y(k)}{\partial w_{pq}} = -\frac{\partial y(k)}{\partial u(k)}\sum_l \frac{\partial u(k)}{\partial O_l^{(3)}(k)}\cdot\frac{\partial O_l^{(3)}(k)}{\partial net_l^{(3)}(k)}\cdot\frac{\partial net_l^{(3)}(k)}{\partial O_p^{(2)}(k)} \times\frac{\partial O_p^{(2)}(k)}{\partial net_p^{(2)}(k)}\cdot\frac{\partial net_p^{(2)}(k)}{\partial w_{pq}(k)} \tag{15}$$

$$\frac{\partial O_p^{(2)}}{\partial net_p^{(2)}(k)} = f'(net_p^{(2)}(k)), \tag{16}$$

$$\frac{\partial net_l^{(3)}(k)}{\partial O_p^{(2)}(k)} = w_{lp}^{(3)}, \tag{17}$$

$$\frac{\partial net_p^{(2)}(k)}{\partial w_{pq}(k)} = O_q^{(1)}(k). \tag{18}$$

Hence, the weights between the input and hidden layer can be calculated from Eqs. (13)–(18).

3.3. *Convergence of the neuro-PID controller*

Rearrange all weights of the neural networks in a line and denote as a vector W, Eqs. (9) and (13) can be summarized as follows

$$W(k+1) = W(k) + \eta \nabla V(W(k)) \tag{19}$$

where $\nabla V(W(k))$ is the gradient of V_k given in Eqs. (10) or (14) evaluated at $W(k)$. Perform the Taylor series expansion of the gradient $\nabla V(W(k))$ around the optimal weight vector W^*

$$\nabla V(W(k)) = \nabla V(W^*) + \frac{\partial \nabla V(W^*)}{\partial W}(W - W^*) \tag{20}$$

Define a new weight vector space $\overline{W} = W - W^*$, it leads to

$$\overline{W}(k+1) = [I + \eta R]\overline{W}(k) \tag{21}$$

where the Hessian matrix $R = \partial \nabla V(W^*)/(2\,\partial W) = \partial^2 V(W^*)/(2\,\partial W^2)$. Let $\Omega = \overline{Q}^T \overline{W}$, $\overline{Q}$ is the orthonormal matrix consisting of the eigenvalues of R. Thus

$$\Omega(k+1) = [I + \eta \Lambda]\Omega(k) \tag{22}$$

where Λ is the diagnonal eigenvalue matrix with entries ordered in corresponding to the ordering in $\overline{Q}$. It yields to

$$\Omega_i(k+1) = [1 + \eta \lambda_i]\Omega_i(k), \quad i = 1,2,\ldots,P(Q+1)+3(P+1) \tag{23}$$

Define $\Delta\Omega_i(k) = \Omega_i(k+1) - \Omega_i(k)$, since the eigenvalues of the Hessian matrix R are negative, $|1+\eta\lambda_i| < 1$ can guarantee that the ith weight of the neural networks obtains a stable dynamics in mean square sense. Therefore, the following inequality can ensure that the proposed algorithm is convergent in mean-square sense.

$$0 < \eta < \frac{1}{max_i|\lambda_i|} \tag{24}$$

This means

$$\lim_{k \to \infty} E\left\{\Delta\Omega_i^2(k)\right\} = 0 \tag{25}$$

where $E(\cdot)$ is mathematical expectation.

4. Design of the improved cascade control system

Fig. 3 shows the schematic diagram of the neural network assisted cascade control system. The inputs to the neural networks should reflect measurable disturbances, the desired and the actual status of the controlled superheated process. The inputs to the neural networks may contain the measurable disturbances besides the feedback error in the outer loop $e_k, e_{k-1}, \ldots, e_{k-\overline{n}}$, because some disturbances, such as steam mass flow, flue gas and attemporator water mass flow, in superheated process can be measured. Therefore, the adaptive neuro-PID controller not only carry out PID feedback control law to deal with disturbances using MEE criterion, but also perform feedforward control law to reject major disturbances if these disturbances can be measured and input to the neural networks.

The procedure to implement the proposed approach is given as follows:

(1) Tune the secondary P or PI controller for inner loop.
(2) Initialize the samples of tracking error to estimate the initial quadratic information potential of the tracking error $V_0(e) = 1/N^2 \sum_{j=1}^{N} \sum_{i=1}^{N} \kappa(e_j - e_i, \sigma^2)$.
(3) Set the receding horizon L and estimate the information potential of the output tracking error in Eq. (3) using the error sequences within the receding horizon window.
(4) Update the weights of the primary neuro PID controller using Eqs. (9)–(18).
(5) Compute the control input in Eq. (4) after obtaining k_p, k_i, and k_d via neural networks.
(6) Apply the control input to the superheated process and collect the superheated steam temperature to recursively update the information potential of the tracking error in outer loop. Then repeat the procedure from Step (4) to Step (6) for the next time step, $k = k+1$.

5. Simulation results

The proposed cascade control approach illustrated in Fig. 3 is applied to regulate superheated steam temperature of a boiler in a 300 MW power plant. In this simulation, the transfer functions of the inertia plant and the leading plant are $G_{\text{plant1}}(s) = 2.09/(1+22.3s)^4$ and $G_{\text{plant2}}(s) = -2.01/(1+16s)^2$ respectively. The primary controller is a neuro-PID controller using MEE criterion and the secondary controller is a proportional controller $G_{C2}(s) = 8$. Some results with a conventional BP neural networks assisted cascade controller are also described for the sake of comparison, in which a conventional neuro-PID controller using MSE criterion is served as the primary controller. The secondary controller is same as that in the proposed approach. The sampling period is $T_s = 1$ s. The distributions of non-Gaussian disturbances ω and ω_2 are shown in Fig. 5.

As far as the proposed neuro-PID controller is concerned, the width of the receding horizon window used to estimate the PDF or information potential of tracking error is set to $L = 200$, the forgetting factor $\lambda = 0.04$, the kernel size $\sigma = 2$ and the learing rate $\eta = 0.0001$. The inputs of the neuro-PID controller include the tracking errors e_k, e_{k-1}, and e_{k-2} and the measured disturbances ω and ω_2. There are five inputs at the input layer of neuro-PID controller ($P = 5$). The number of the hidden nodes is selected experimentally to be $Q = 4$. The difference between the proposed neuro-PID controller and conventional neuro-PID controller are the criterion to training neural networks, both neuro-PID controllers have same structure and parameters.

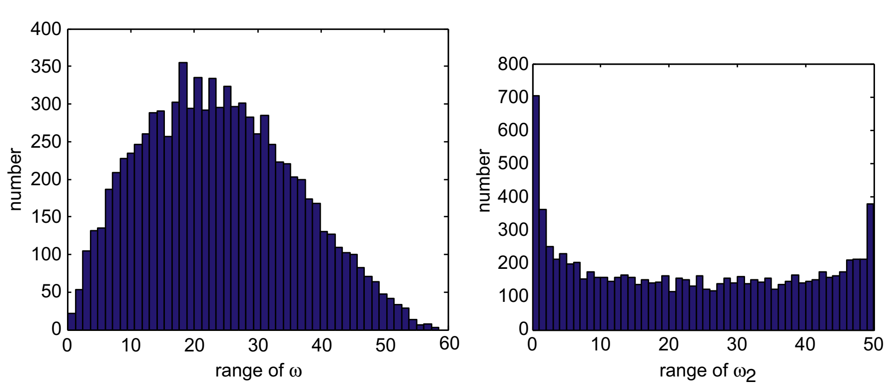

Fig. 5. Distributions of disturbances ω and ω_2.

The superheated process operates at a steady state before 500 s, the set point of the superheated steam temperature increases from 535 °C to 545 °C at 500 s and lasts forever, the response of the superheated steam is shown in Fig. 6, it can be seen that both approaches can stabilize the superheated temperature around the set point with small oscillation. The dot line is the response of superheated steam temperature using the neuro-PID controller under MSE criterion, in which the mean value and standard deviation are 0.5093 and 1.7153 respectively. On the other hand, the solid line in Fig. 6 indicates the response of superheated steam temperature using the proposed neuro-PID controller under MEE criterion, and the mean value and standard deviation are 0.4452 and 1.7049 respectively. It can be seen that the fluctuation of superheated steam temperature is smaller using the proposed neuro-PID controller under MEE criterion. Fig. 7 shows that the proposed neuro-PID controller's parameters have smaller uncertainties than that of the neuro-PID controller under MSE criterion. Fig. 8 demonstrates that the entropy of tracking error using the presented cascade control is smaller than that using cascade control system with the primary neuro-PID controller under MSE criterion. It can be seen that the control input is driving the system towards a smaller randomness direction. Likewise, this can also be verified in the 3-D mesh plot in Figs. 9, 10 and 11. Compared Fig. 9 with Fig. 11, the shape of the PDF of tracking error in Fig. 11 becomes narrower and sharper along with sampling time, it indicates that the proposed cascade control system has a small uncertainty in its closed loop operation. It also can be verified from Figs. 10 and 12 in which the PDF of tracking error at several typical instants using MSE-NNPID and MEE-NNPID algorithm respectively. Therefore, the simulation results are consistent with the theoretical analysis.

The proposed cascade control scheme exhibits a satisfactory performance that achieves a narrow and sharp distribution of tracking error which corresponds to small entropy of tracking

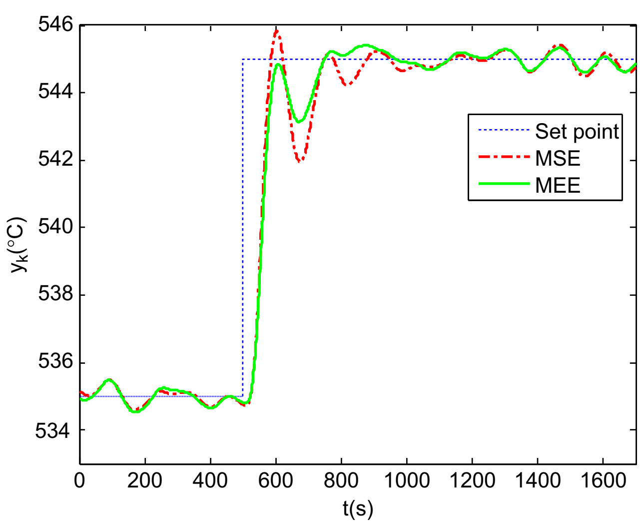

Fig. 6. Responses of the superheated steam temperature.

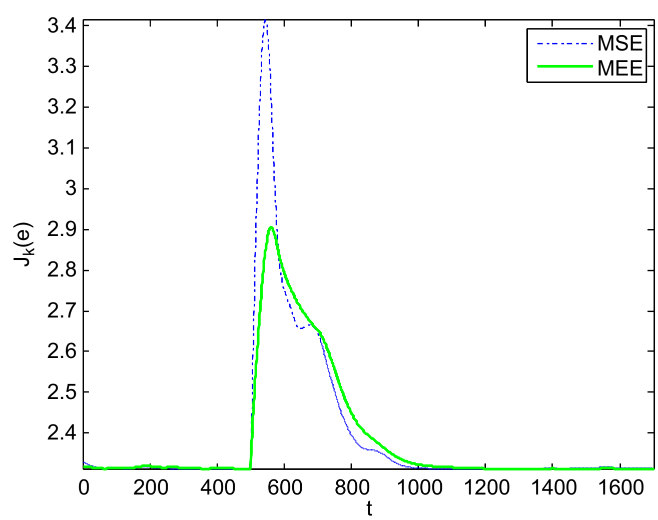

Fig. 8. Performance index.

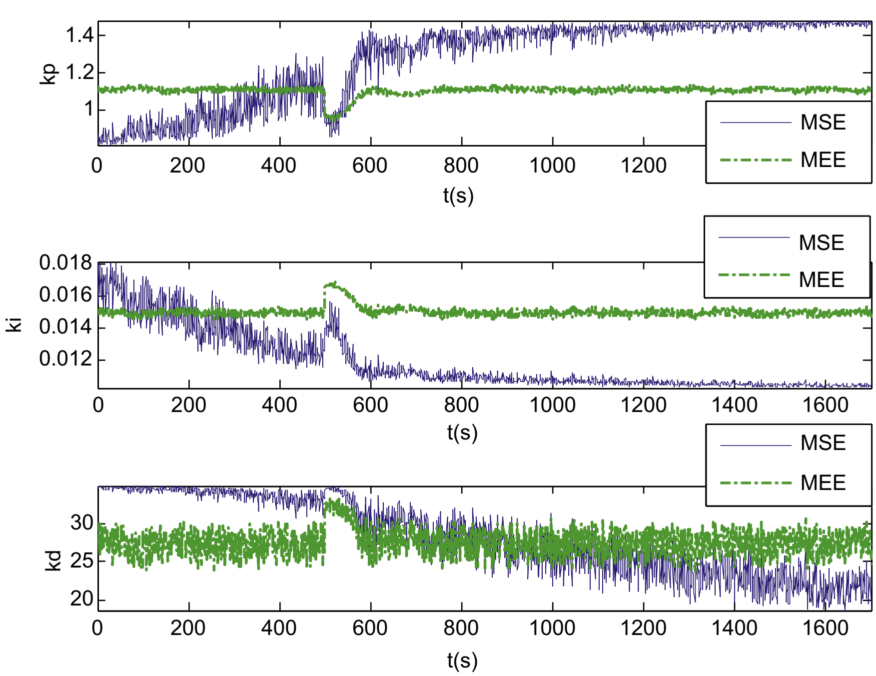

Fig. 7. Parameters of primary PID controller.

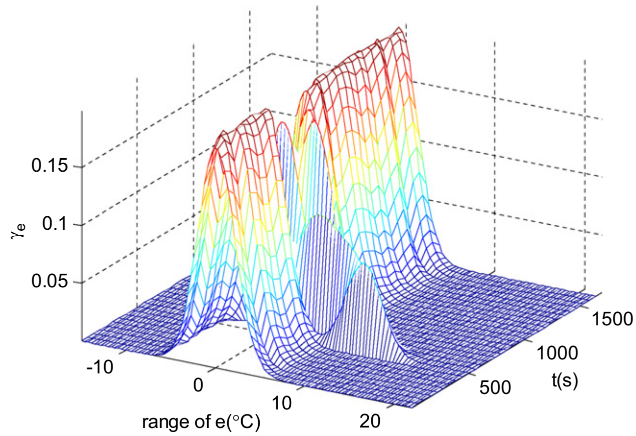

Fig. 9. PDF of error (MSE-NNPID).

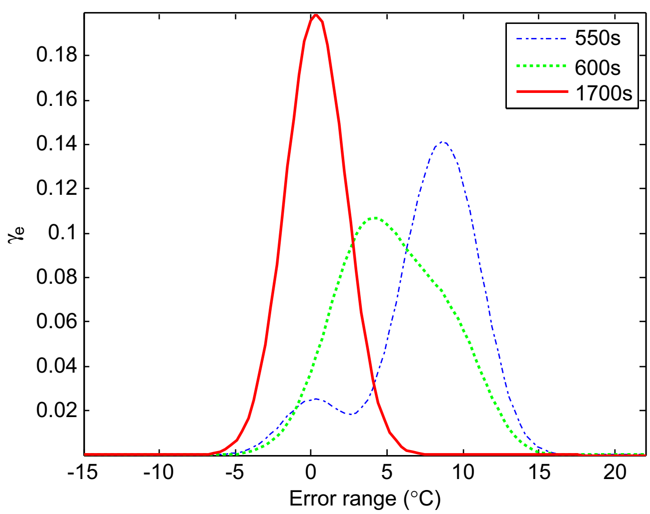

Fig. 10. PDFs at typical instants (MSE-NNPID).

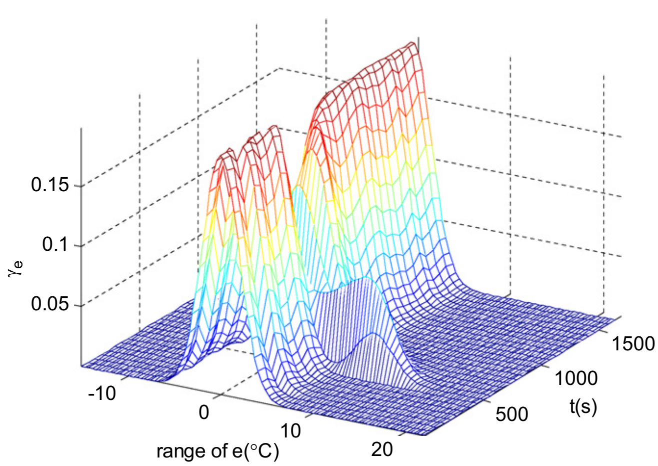

Fig. 11. PDF of error (MEE-NNPID).

error. On the contrary, when the conventional neuro-PID controller under MSE criterion is served as the primary controller, the dispersion of tracking error is bigger.

The above simulation results indicate how well the proposed control scheme performs. It is concluded that the proposed neuro-PID controller makes full use of the MEE criterion to obtain

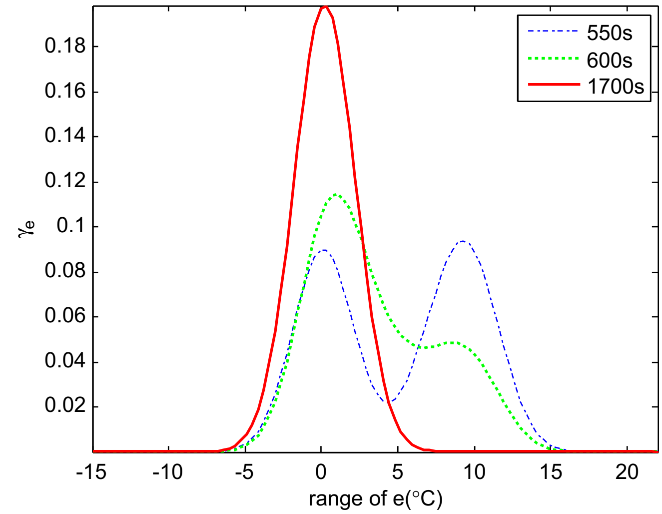

Fig. 12. PDFs at typical instants (MEE-NNPID).

improved performance over the conventional neuro-PID controller using MSE criterion.

6. Conclusions

In this paper, a minimum entropy based neuro-PID controller is presented as primary controller in the cascade control system for regulating superheated steam temperature in power plants. The performance index to train neural networks of the outer loop system uses the entropy or information potential of tracking error rather than the squared error. The information potential of the tracking error can be estimated recursively by employing the receding horizon window technique. The training algorithm of neuro-PID controller is derived and the convergence of the neural networks is analyzed. Moreover, the implementation of the proposed cascade control approach is developed. This approach not only overcomes the tedious tuning for the PID controller, but also makes the control system adaptive and robust.

Since the measurable disturbances can be input to the neural networks besides the sequences of the tracking error, the proposed neuro-PID controller under MEE criterion integrate feedback with feedforward control law. In addition, not only the primary controller but also the secondary controller rejects disturbances. Even if there are some non-Gaussian disturbances in superheater processes, the presented control strategy can achieve small entropy, it means the fluctuation of steam temperature is less, and accordingly a higher set-point can be set. Obviously, mechanical stress causing micro-cracks can be prevented and the average efficiency of the turbine can be increased.

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