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Review of Control Strategies Employing Neural Network for Main Steam Temperature Control in Thermal Power Plant

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Abstract

Main steam temperature control in thermal power plant has been a popular research subject for the past 10 years. The complexity of main steam temperature behavior which depends on multiple variables makes it one of the most challenging variables to control in thermal power plant. Furthermore, the successful control of main steam temperature ensures stable plant operation. Several studies found that excessive main steam temperature resulted overheating of boiler tubes and low main steam temperature reduce the plant heat rate and causes disturbance in other parameters. Most of the studies agrees that main steam temperature should be controlled within ±5 Deg C. Major factors that influenced the main steam temperature are load demand, main steam flow and combustion air flow. Most of the proposed solution embedded to the existing cascade PID control in order not to disturb the plant control too much. Neural network controls remains to be one of the most popular algorithm used to control main steam temperature to replace ever reliable but not so intelligent conventional PID control. Self-learning nature of neural network mean the load on the control engineer re-tuning work will be reduced. However the challenges remain for the researchers to prove that the algorithm can be practically implemented in industrial boiler control.

Keywords: Main steam temperature; thermal power plant; neural network

■1.0 INTRODUCTION

In thermal power plant, keeping the process parameters according to its setpoint is paramount to ensure stabil operation of the plant. One of the most important thermal power plant parameters is main steam temperature (MST)[1]. The steam temperature must be control within the specified limit to maintain plant nominal efficiency as well as ensuring safety for the plant equipment especially boiler tubes[2]. Successful control of MST also ensures stable load dispatch. What makes so difficult to control main steam temperature is it behavior which is non-linear, large inertia, long dead time and load dependent. It means daily load changes from 100% to 30% will have the effect to main steam temperature and the change is non-linear[3]. Typical controller applied at thermal power plant is cascade PID control. Main steam temperature control is paramount in ensuring lifetime of the plant equipment, efficiency, load following capability and availability[4]. Too high temperature will result damages to boiler tubes due to thermal shocks. Too low temperature cause instability for other parameters especially main steam pressure and reheater steam temperature which subsequently cause the unit unable to achieve required load. PID controller is selected in various industry applications due to its simple architecture and robustness. However PID controller has some drawbacks. One of the disadvantages of PID controller is the determination of Kp, Ki and Kd which is based on heuristic approach which require experience and knowledge. Person who tries to do the tuning need advance knowledge both in control and process. Furthermore, it is also impossible to realize perfect performance for the controller for all plant behavior that might happen[2]. This paper will review control strategies employing neural network and fuzzy techniques that has been tested as an alternative for PID controller for main steam temperature control in a thermal power plant.

■2.0 NEURAL NETWORK (NN)

Starting from 18th century, human being already starts thinking of building intelligent machine. However it is not until the 20th century that the study of neuro science start gaining its pace and human start to understand further about human brain and try to replicate it[5]. Santiago Ramon y Cajal introduced important conceptual insight that the nervous system is made up of discrete signaling elements called neurons[5]. However actual breakthrough in neural network came in 1943 when McCulloch and Pitts published their paper that introduced term "Boolean Brain"[6].

Because of the "all-or-none" behavior for nervous activity, any neural events and its relation can be treated by Boolean logic[6]. There are many progress in understanding human brain and reflected it to artificial neural network but one of the most significant work is by John von Neumann which reflected McCulloch and Pitts ideas during the design of first digital computers. John von Neumann discussing the comparison between computing machines and living organisms, where both displaying the "all-or-none" behavior[7]. Around the same time, Hebb's publication in 1949 introduced several hypotheses about the neural substrate of learning and memory which is famously known as Hebb's learning rule or Hebb's synapse[8]. Hebb's publication continues to spur more work on neural network and inspire diverse computational neural network models. Turing Test which was introduced by Alan Turing in 1950 suggested that computer can be considered intelligent if a human communicating by teletype fail to differentiate the computer from the human being[9]. Not until publication of Rosenblatt's Perceptron that the area of neural network research receives a huge boost. Rosenblatt's demonstrate his algorithm capability of pattern recognition that could learn, the convergence proof of Perceptron learning scheme and its ability to classify linearly separable pattern classes[10-13]. Rosenblatt's model further refined by Minsky and Papert in the 1960s; its computational properties were thoroughly analyzed[14]. Since then, there is numerous researches in neural network areas convene and many neural network models are introduced.

■3.0 APPLICATION OF NEURAL NETWORK IN MAIN STEAM TEMPERATURE CONTROL IN THERMAL POWER PLANT

There has been significant interest in applying NN in thermal power plant because of NN ability to self learning and fast convergence to the target. Neural Network intelligent PID control system based on immune GA and back-propagation (BP) neural network is discussed in[15]. The proposed method combined the advantage of global search optimization ability of GA, the weight optimization capability of neural network and at the same time adjusting PID parameters using backpropagation learning. The method proves superior to conventional PID control system in controlling main steam temperature.

The method of least square support vector machines based on radial basis function to control main steam temperature is introduced in[16]. It is found out the dynamic response of main steam temperature are caused by main steam flow, main steam pressure and temperature. From the result it is shown that the proposed method is effective.

The proposed combination of PID cascade control with BP learning algorithm neural network is discussed in[17]. The proposed method has the BP algorithm advantage of fully approximate complex non-linear mapping, learn and adapt the dynamic characteristic of the system as well as PID cascade fast response time. The testing was made using MATLAB simulation and the effect of implementing it on the actual plant is yet to be investigated.

Credit assigned Cerebellar Model Articulation Controller (CA-CMAC) is used to control main steam temperature control in[18]. CA-CMAC is further enhancement version of CMAC neural network which speed up the learning process in CMAC. The proposed controller is applied through MATLAB simulation and the result shows the CA-CMAC converges faster than conventional PID and pure CMAC. Furthermore, it has smaller overshoot, strong interference immunity and good adaptive performance.

Expanded-Structure Inverse Dynamic Process Models (IDPM) for 300MW main steam temperature process are developed using backpropagation learning algorithm neural networks in[19]. The output for IDPM controller are the first and second stage spraywater control valves opening. The neural network structure used was 16 no. of input neurons, 15 no. of neurons in hidden layer and 1 neuron on output layer. Based on trained IDPM models, neural network inverse compensation controller are constructed to be implemented on online main steam temperature control. The proposed controller is then tested on full scope simulator through UDP/IP protocol. The test result showed that the proposed controller performed better in term of controller speed and overshoot in comparison with existing PID cascade control.

Mixed-Structure Recurrent Neural Network Models for 600MW supercritical main steam temperature process is constructed in[20]. The model is then used as part of simple Particle Swarm Optimization (sPSO) algorithm to control final superheater outlet steam temperature. The proposed controller is then tested on full scope high fidelity simulator. The result was compared with conventional PID control. The proposed controller is proved to have better control performance especially ender wide-scope load changing conditions.

The online tuning of PID using Particle Swarm Optimization (PSO) and backpropagation neural network learning algorithm is discussed in[21]. The combination of PSO and BP neural network to provide self-tuning element to PID control enhance existing PID control. The proposed method is simulated to control main steam temperature at thermal power plant. The result showed the proposed strategy improved existing control and have good anti-jamming performance.

Daogang Peng *et al*. claimed in[22] that the control method of immune PID cascade control that is applied to main steam temperature control in thermal power plant based on self learning of the neural network parameters is better than traditional PID method. The method also can adapt to changes of the parameters as well as strong robustness. However the work by Daogang Peng *et al.* is based on simulation and never been tested on actual thermal power plant. No reference data shows to verify and support the effectiveness of the control.

The expanded structure inverse dynamic process models for superheater steam temperature are established based on dynamic recurrent neural network in[23]. The proposed controller is applied at 600MW supercritical boiler. The neural network is then trained using improved Leverberg-Marquadt algorithm. The output of the neural network is then become supplementary action together with existing cascade PID control. The controller performance is verified through its application on the 600MW supercritical boiler full scope high fidelity simulator. The proposed control scheme shows great improvement in control speed and overshoot of the superheater steam temperature.

The control strategy which combines RBF (radial basis function) neural network tuning PID and fuzzy immune control to superheat temperature control at thermal power plant is discussed in[24]. The control has stronger robustness and better self-adaptive ability to the control parameter. The study was done on supercritical plant superheat temperature control.

The implementation of Cerebrum Model Articulation Controller (CMAC) neural network as part of main steam temperature control is discussed in[25]. CMAC Neural Network is a network association of only a small portion of each of the output neurons (the input decision) related to its association with local generalization, also known as the promotion of capacity, which is similar to the input and it will produce output similar to, and input from the output generated almost independent. The proposed controller used CMAC as feedforward control and single neuron

PID with quadratic index as a feedback. The proposed controller implemented to supercritical boiler superheater and from the result it shows that the controller is effective in controlling MST and has some self adaptive adjusting capability.

Neural network predictive control scheme utilizing multi-step prediction, rolling optimization and feedback correction control strategy utilizing backpropagation learning algorithm is presented in[26]. The proposed control scheme was introduced to control main steam temperature in a 600MW supercritical plant. The test was carried out using MATLAB environment. The test result showed the proposed control scheme show better control in both static and dynamic performance and better robustness.

Neural network models using real plant data to predict steam properties including main steam temperature is discussed in[27]. It is proposed that operational data continuously captured by the online plant monitoring system is used as a basis to construct neural network models.

Principal of component analysis (PCA) was used to filter the raw data to be used as the inputs for neural network in[28]. The neural network algorithm was then implemented to control main steam temperature. There were 2 neural network algorithms implemented, using filtered inputs from PCA and using raw field data. The test showed both sets of input resulted nearly the same output for the main steam temperature. It can be concluded from the test that PCA can be used to filter the raw field data before became the input for neural network algorithm. It significantly reduced the computational times since PCA already filtered unwanted and 'noise' data.

Generalized PID Neural Network (GPIDNN) to control main steam temperature was discussed in[29]. It is multi-layer forward type neural network with backpropagation learning algorithm. The proposed control scheme demonstrates it is less sensitive to variation in time-delay in comparison with conventional PID. Furthermore it has short transition time and ideal control quality.

Self-tuning PID neuro controller utilizing gradient algorithm is proposed in[30]. The Jacobian information of the plant is then obtained through Radial Basis Function (RBF) neural network. The proposed control scheme is then tested to control main steam temperature on 600MW supercritical power plant. To demonstrate the effectiveness of the proposed control scheme over wide range operation, the testing was done during loading up from 300 MW to 450 MW and also loading down 450 MW to 300 MW. The simulation result showed the proposed control scheme performed better in term of parameters stability on wide range operation.

Single neuron Proportional, Summing and Differencing (PSD) self adaptive algorithm which based on Smith predictor was discussed in[31]. The single neuron is an elementary unit in artificial neural network which have advantages of simpler structure, simpler computation and can satisfy real time control in practice. The proposed scheme was tested using MATLAB environment. The result showed it does not need precise identification of variables and also can compensate the disadvantages of Smith predictor in uncertainty system.

Aiming at to control main steam temperature in 300 MW thermal power plant, an adaptive inverse control based on parallel self-learning neural network is proposed in[32]. The proposed control scheme includes two main structure; main control system and parallel self-learning system. The main control system consists of the plant, neural network identification model (NNM), neural network inverse controller (NNC) and robust feedback stabilize controller (RC). RC produce a feedback signal by a system error to ensure the continuity of the closed loop system and this action complement NNM weakness which can't be trained well enough especially at initial stage. The proposed control scheme showed it has better control than conventional PID and also very robust.

A neural network model-based nonlinear Long Range Predictive (LRP) multivariable controller is proposed by Prasad, Swidenbank and Hogg in[33]. The proposed controller is applied to simulated drum boiler type, 200 MW oil fired power plant to control 3 variables, main steam temperature, reheat steam temperature and main steam pressure. The result of the simulation shows that the proposed controller successfully maintains all the parameters within the stipulated limit. However, the controller was not tested on the actual power plant operation.

Xianzhong Cui and Kang G. Shin in[34] propose neural network (NN) as an adaptive controller for main steam temperature control at supercritical boiler as a replacement for PI control. The authors utilize BP learning method to train the NN algorithm. Similar technique has been used in other publication elsewhere.[35] What is unique about the training algorithm is that the NN is trained with system output errors instead of network output errors that is frequently proposed. The simulation result shows that NN controller is performing better than typical PI controller. Adding more hidden layer also does not necessary improve the system performance but definitely improve the system reliability.

4.0 DISCUSSION

The review showed that main steam temperature control in thermal power plant has been the popular research subject for the past 10 years. The complexity of main steam temperature behavior which depends on multiple variables makes it one of the most challenging variables to control in thermal power plant. Furthermore, the successful control of main steam temperature ensures stable plant operation. Various papers discussed that too high main steam temperature resulted overheating of boiler tubes and too low temperature reduce the plant heat rate and disturbance in other parameters. Most of the papers agrees that main steam temperature should be controlled within ±5 Deg C. Major factors that influenced the main steam temperature are load demand, main steam flow and combustion air flow. Most of the proposed solution embedded to the existing cascade PID control in order not to disturb the plant control too much.

Neural network controls remains to be one of the most popular algorithm tested to control main steam temperature to replace ever reliable but not so intelligent conventional PID control. Researchers prefers to use neural network due to self-learning capability of the method.

However it is important to note that most of the researches carried out utilizing the algorithm are simulated using engineering software namely MATLAB and MATHEMATICA. Thus questions can be asked on the application of these algorithms to actual thermal power plant. One of the most important challenges for these algorithms to work in industrial set up is the response speed of the algorithm; which also depends on the hardware used. The algorithm need time to compute the output and industrial process is a continuous, dynamic and fast reaction. Thus there is possibility of response lag between the output of the algorithm and the actual process.

5.0 CONCLUSION

Based on the review, it is easy to note that main steam temperature remain one of the most difficult parameters to control in thermal power plant. This cause many researchers interested to improve the control which currently using cascade PID control. Neural network control are one of the most popular alternative solution for main steam temperature control. Self-learning nature of neural network mean the control engineer re-tuning work is reduced. However the challenges remain for the researchers to prove that the algorithm can be implemented to industrial boiler control.

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