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A Novel Approach to Performance Prediction of Boiler Parameters in Thermal Power Plants using Soft Computing Techniques

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Abstract:
Soft computing techniques are being increasingly applied to predict parameters relating to the performance of boilers in thermal power plants. In this paper a combination of Genetic Algortihms (GA) and Artificial Neural Networks (ANN) are used for performance prediction of boilers. An implementation of Genetic algorithms, called Gene Hunter is used for feature selection. A threshold of value 0.1 was identified and features whose importance exceeded 0.1 were taken as the selected features. For the ANN, Superheater spray and Reheater spray which perform the primary role of controlling the main steam/reheat temperature and NOx are chosen as the output parameters. In this paper cascade correlation algorithm has been used to predict parameters of Reheater Spray, Superheater Spray and NOx. It is a novel approach that automatically adds new hidden neurons one by one and fixing the network topology once training is done. Turboprop 2, a variant of the cascade correlation algorithm has been used for this purpose. The overall results were of the order of 99.6%, 98.6% and 91.6% for RH Spray, SH Spray and NOx respectively.

Keywords: *ReHeater Spray, Super Heater Spray, NOx, Artificial Neural Networks, Genetic Algorithms, Feature Selection, Cascade Correlation*

1. Introduction

The Reheater section in a utility boiler improves the efficiency of the thermal power plant by reducing losses. It absorbs heat from the flue gases before their exit, adds to power generation through IP & LP turbines and reduces the temperature & pressure of steam before sending it to the condenser. Reheater spray is normally provided at the inlet of reheater in the cold reheat pipe. Reheater spray control is used to supplement the burner tilt control when the primary control system (control of fuel and air injection) is not able to regulate the temperature to the required level. The reheater spray control helps in increasing the overall steam flow while keeping the metal temperatures under control, however it has negative effect on unit heat rate. Reduction in Superheater and Reheater spray usage leads to optimising the plant heat rate. Limited use of Superheater spray with maintained water quality will ensure that the nozzles of the Desuperheater are not corroded. Overheating failures [1]occur in the sections preceding the Desuperheater due to metal temperature going higher. Corrosion and thermal fatigue also occurs with the deposition of salts by water particles after complete evaporation. In order to increase the life span of the equipment and also to maintain optimum heat rate, the sprays should be maintained within limits. With increased environmental regulations on emissions, NOx emissions have to be maintained at 100 mg/Nm^3 for plants installed from 1st January 2017. This places an increased onus on power plant manufacturers to deliver equipment that conforms to these regulations. The work done in this paper is an attempt to monitor SH Spray, RH Spray and NOx.

2. Illustrations of Reheater and Superheater Spray Control Mechanisms

The Superheater and Reheater spray control have inherent architectures built in to achieve the temperature control. In some power plants there are more than one reheater to increase the capacity. The figures 1 and 2 illustrate reheater and superheater spray control mechanisms.

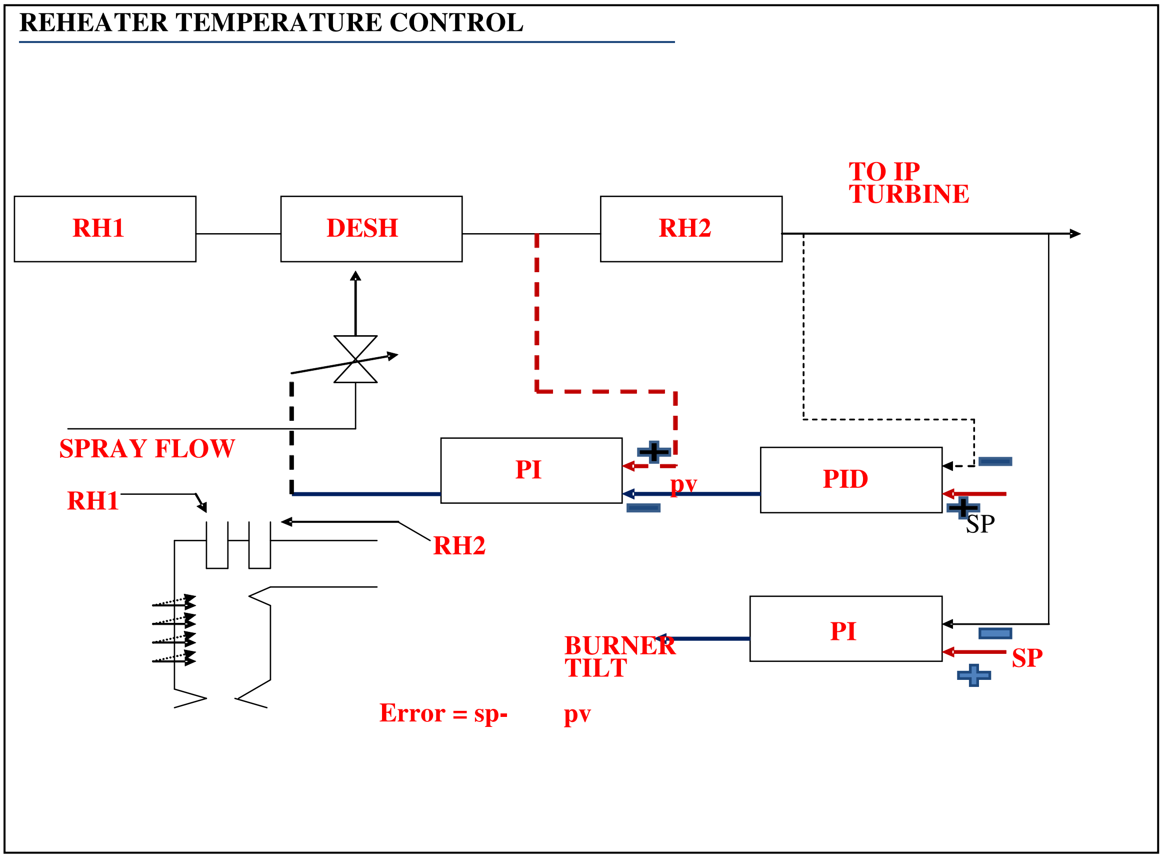

Figure 1: Illustration of Reheater temperature control with two reheaters

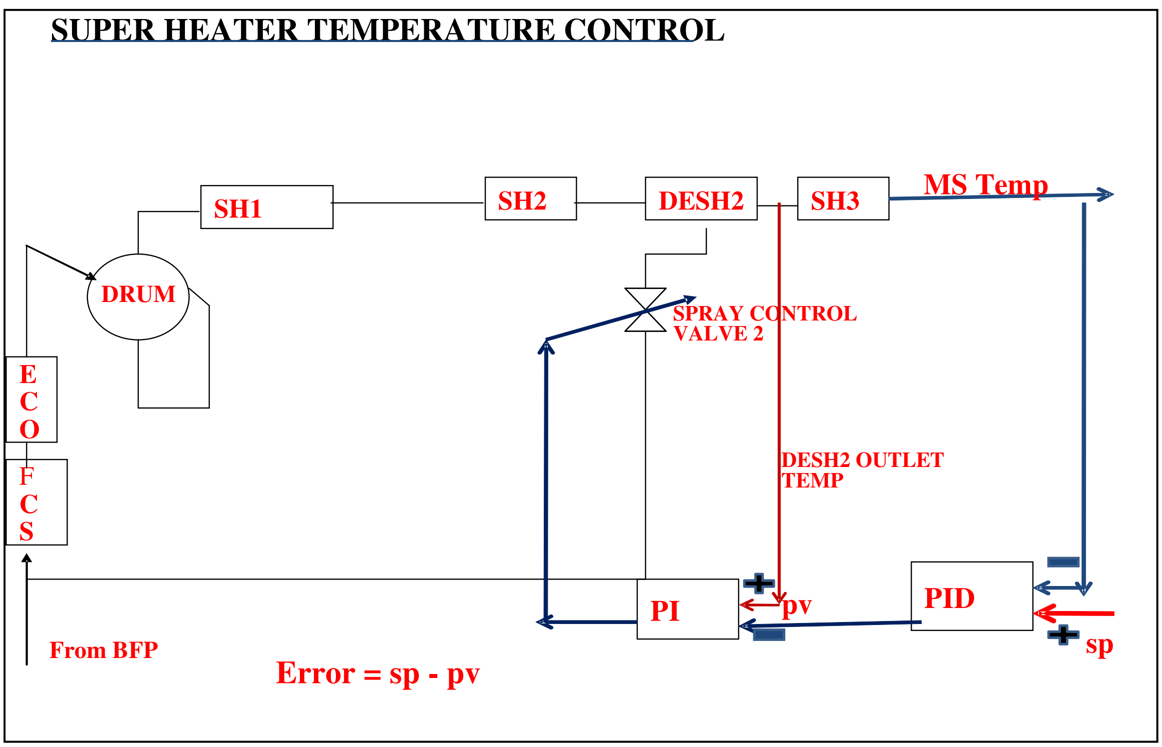

Figure 2: Illustration of superheater temperature control with three superheaters

3. Overview of the Approach Used

The Initial features are selected using GeneHunter [2], a genetic algorithm implementation. About 15 input features have been used based on the data available from tests. These features were fed into a genetic algorithm with a statistical estimator to produce a model which shows the usefulness of inputs. The aim was to maximize the coefficient of multiple determination in a minimum number of generations. A threshold value of 0.1 was used to determine which features had a relative importance over the others. A list of 4 features each were identified for RH Spray, SH Spray and NOx. These 4 features were then taken as input to the Artificial Neural Network. The ANN is based on the principle of cascade correlation wherein hidden neurons are generated based on the need for the topology and subsequently frozen. The output of the ANN is RH Spray or SH Spray or NOx as the case may be, but one at a time. Figure 3 indicates the overview of the approach used.

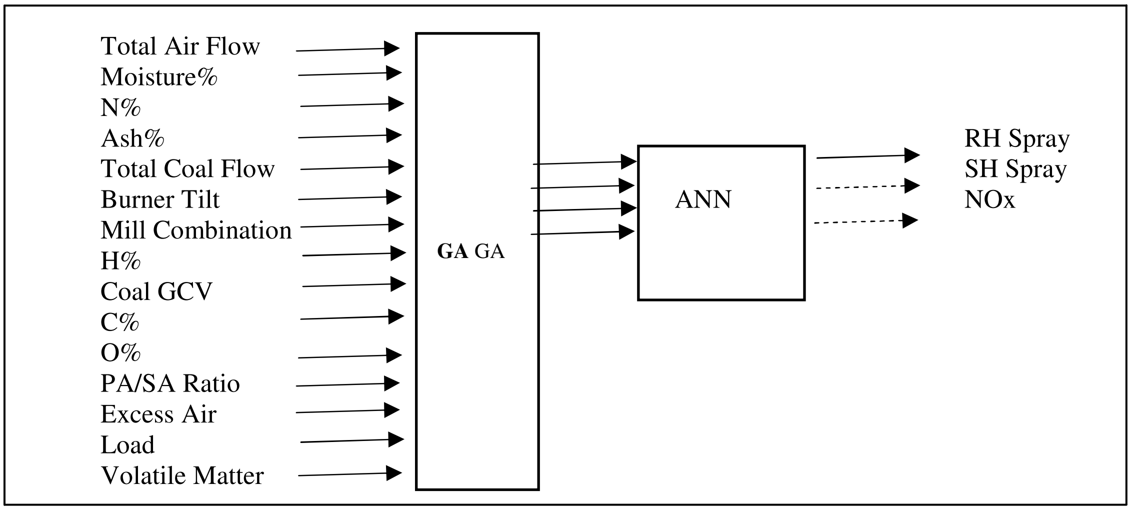

Figure 3: Block Diagram of the Approach

4. Feature Extraction Using Genetic Algorithm

Based on pre-processing, about 15 different features relating to proximate and ultimate analysis of coal, based on coal quality and other important features relating to combustion have been taken as the universal set of features. Mill combination was taken as a binary string in which mills fired were represented by ‘1’ and the mills not fired were represented by ‘0’. The topmost mill was made the most significant bit. The ratio of primary air to secondary air was calculated. Coal quality data from proximate and ultimate analysis was converted from air-dried basis to as fired basis. These were then run through a genetic algorithm implementation called GeneHunter based on the one developed by David Goldberg. The genetic algorithm gave a list of features based on their relative importance to the output under consideration, i.e. reheater spray, superheater spray and NOx. Table 1 shows the results of the genetic algorithm based on the sensitivity of the features [2].

S. No.	Feature	Sensitivity to RH Spray	Sensitivity to SH Spray	Sensitivity to NOx
1.	Total Air Flow	0.141	0.129	0.12
2.	Moisture%	0.131	0.109	0.137
3.	N%	0.123	0.085	0.131
4.	Ash%	0.122	0.109	0.093
5.	Total Coal Flow	0.104	0.067	0.053
6.	Burner Tilt	0.087	0.123	0.043
7.	Mill Combination	0.069	0.013	0.014
8.	H%	0.058	0.05	0.134
9.	Coal GCV	0.057	0.073	0.034
10.	C%	0.039	0.069	0.004
11.	O%	0.033	0.054	0.074
12.	PA/SA Ratio	0.026	0.049	0.053
13.	Excess Air	0.01	0.042	0.051
14.	Load	0.001	0.013	0.036
15.	Volatile Matter	0	0.012	0.024

Table 1: Feature Sensitivity through genetic algorithm

Four different features based on their relevance and relative importance were then extracted for each of reheater spray, superheater spray and NOx prediction. These were decided as final features extracted for the training exercise to be done through artificial neural network. Total Air Flow, Moisture%, Ash%, Total Coal Flow were chosen as inputs for Reheater spray prediction. Total Air Flow, Moisture%, Ash% and Burner Tilt were chosen as inputs for Superheater spray prediction and Total Air Flow, Moisture%, N% and H% were chosen as inputs for NOx prediction.

5. Training of Artificial Neural Network through Cascade Correlation

Once the input-output features were identified, they were trained through an artificial neural network that is based on the principle of cascade correlation algorithm. Cascade-Correlation is a supervised learning algorithm for artificial neural networks and has a novel architecture as compared to conventional back-propagation. Cascade-Correlation begins with a minimal network, then automatically trains and adds new hidden neurons one by one, creating a multi-layer structure. It is not based on fixed topology of hidden neurons. Once a new hidden neuron has been added to the network, its input-side weights are fixed. The Cascade-Correlation architecture has several advantages over existing algorithms [3]. It learns very quickly. The network determines its own size and topology. The network retains the structures it has built even if the training set changes, and it requires no backward pass of error signals through the connections of the network. It is a purely feed-forward network. The goal of this algorithm is to maximize S, the sum overall output unit's*o* of the magnitude of the correlation (or, more precisely, the covariance) between V, the candidate unit's value, and Eo, the residual output error observed at unit *o*. we define S as[3]

$$S = \sum_{o}\left|\sum_{p} (Vp - V)(Ep,o - Eo)\right| \ldots (1)$$

where,*o* is the network output in which the error is measured and *p* is the training pattern. The quantities V an Eo are the values of V and Eo averaged over all the patterns. Our aim would be to maximize S.

The scatter plots after training for each of the outputs independently are shown in figures 3,4,5.

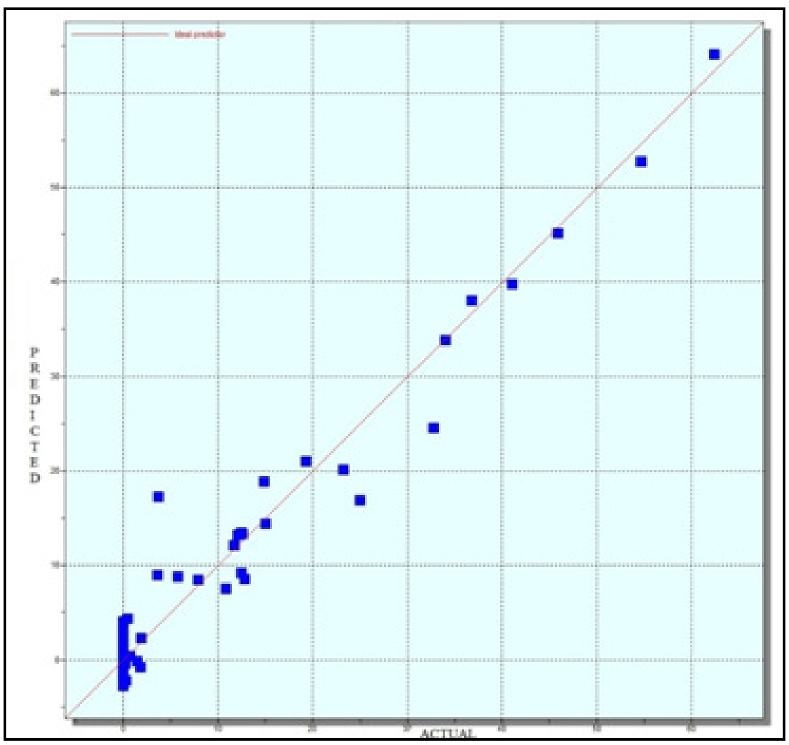

Figure 4: Reheater Spray Prediction

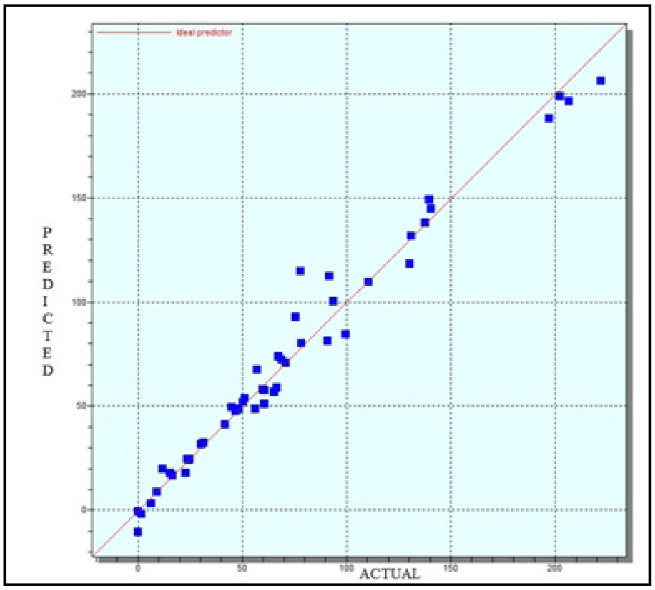

Figure 5: Superheater Spray Prediction

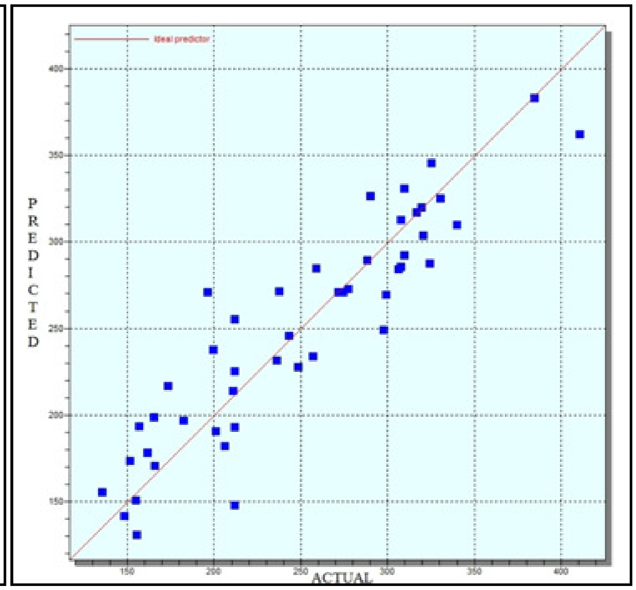

Figure 6: NOx Prediction

6. Analysis of the Results Obtained

The Reheater spray prediction was achieved with a correlation coefficient of 99.6675 and a performance of 1.65. The performance is a measure of the mean square error. The superheater spray prediction was achieved with a correlation coefficient of 98.6884 and a performance of 82.06. The NOx prediction was achieved with a correlation coefficient of 91.693 and a performance of 746.0605. Though the NOx prediction has a lower correlation coefficient, it generalises well and predicts better for new data sets. Overall all the three networks have a good generalisation capability. Results of cross validation for reheater spray, superheater spray and NOx indicate a generalisation quotient of within 6% independently [4]. But this does not mean that the generalisation quotient will be uniform for all the new data sets.

7. Future Work and Conclusions

The present work has been mainly focussed on methods of effective monitoring of reheater spray, superheater spray and NOx. The future work would be to engage in online monitoring and prediction of these parameters. Reheater spray, superheater spray and NOx are effective indicators of boiler performance. They have to be minimised in order to optimise heat rate as well as regulate emissions which would in the long run lead to better performance of boilers. The present study may be extended to supercritical boilers as well.

8. Acknowledgements

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9. References

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