2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

Optimization of Incinerator Controllers using Artificial Neural Networks

Kenneth J. Mackin[1] Ryutaro Fukushima[2] Makoto Fujiyoshi[2]
[1]Department of Information Systems, Tokyo University of Information Sciences
1200-2 Yatoh-cho, Wakaba-ku, Chiba, Japan
[2]Hitachi Zosen Corporation
1180 Amarubekami, Maizuru-shi, Kyoto, Japan
email: mackin@rsch.tuis.ac.jp, {fukushima_r, fujiyoshi_m}@hitachizosen.co.jp

***Abstract* - The emission of dioxins from waste incinerators is one of the most important environmental problems today. It is known that optimization of waste incinerator controllers is a very difficult problem due to the complex nature of the dynamic environment within the incinerator. In this paper, we propose applying artificial neural networks to waste incinerator controllers. We show that artificial neural networks can project the emission of dioxins with a fair degree of accuracy**

I. INTRODUCTION

Dioxyne emission from waste incinerator plants is one of the hottest ecological problems today. Fujiyoshi et al [1] has proposed applying fuzzy control to incinerator control to decrease the dioxyne emission.

In waste incinerator plants, the chemical reactions in the incinerator occur under a very dynamic environment, making its control is a very complex task, and current state-of-the-art incinerator facilities have not succeeded in completely removing the dioxyne emission.

The volume, density and contents of the garbage to be incinerated are not constant, so it is impossible to control the combustion as in a laboratory environment. One of the causes of dioxyne emission in waste incinerator plants is due to the fluctuations in the amount of garbage fed in the incinerator. The fluctuation in garbage fed leads to temporary deterioration of the combustion state (i.e. oxygen rate), and short peaks of dioxyne emission occur.

For this research, we investigate methods applying neural networks for the prediction of dioxyne emission as well as for the combustion control to decrease the dioxyne emission, and plan to continue this approach in applying the proposed method to real incinerator plant controllers.

II. TRAINING REQUIREMENTS FOR WASTE INCINERNATORS

For this research, we used real waste incinerator data provided by Hitachi Zosen Corporation. Fluidized bed incinerator data from the Ryotsu City Clean Center in Niigata prefecture, Japan, was used.

The data consists of the following sensor values measuring various conditions of the incinerator. Flapper angle(0～100.00%), oxygen concentration in incinerator exit (0 ～ 25.000%), garbage rate(t/H), incinerator temperature(0～1200.0℃), carbon monoxide concentration(0 ～ 500.0ppm), incinerator pressure(-2000.0 ～ 1000.0ppm), cooling liquid rate(0～1.0000m3/h), conveyer belt speed(0 ～ 7.000rpm), primary air supply(0 ～ 7.500KNm3/h), secondary air supply base(0 ～ 7.500Nm3/h), secondary air supply modification(0 ～7.500KNm3/h).

The flapper is lifted as garbage is carried by the conveyer belt, and the flapper angle is used as the measure of garbage volume. The above sensor data was collected in approximately 2 second intervals.

It is known that CO (carbon monoxide) concentration shows strong correlation with dioxyne concentration at over 100ppm. For this research, we use the CO concentration as the target output, and aim to reduce the average CO concentration as well as to reduce the number of CO concentration peaks over 100ppm.

From the collected data, it can be observed that when the flapper angle (garbage volume) increases, after a time delay the oxygen concentration decreases, and after further time delay the carbon monoxide concentration increases. This can be understood by the following explanation. The increased garbage measured by the flapper takes some time before arriving at the incinerator. The increased garbage in the incinerator increases the combustion and consumes more oxygen, which lowers the oxygen concentration. The temporarily decreased oxygen concentration deteriorates the combustion state and a peak in carbon monoxide occurs due to imperfect combustion. Since the carbon monoxide sensor is placed at the incinerator emission, the peak in carbon monoxide concentration is displayed after a further time delay.

From the above observation, for this paper we especially concentrate on flapper angle and oxygen concentration as input.

III. INCINERATOR CONTROL USING ARTIFICIAL NEURAL NETWORKS

For each of the different types of incinerator sensor data, there is an apparent correlation just described, but direct correlation between the sensor data and carbon monoxide concentration is not very strong. This is because the environment in the incinerator is a complex dynamic environment in which the different items are dependent on each other, and is not a simple dependency relationship.

Artificial neural networks can be characterized by its "black box" approach to learn and classify complex data patterns. For this research, we propose applying artificial neural networks in incinerator control, using the ANN to learn the complex relationship between incinerator sensor data.

For the neural network structure, we plan to consider various network structures, but for the first stage we will work with a standard 3 layer feed forward network using BP (backward propagation) training. We will consider other network structures such as recurrent networks, and neural network classifiers without training sets in future works.

The proposed incinerator controller training system using artificial neural networks is divided into 2 sections, the dioxyne prediction section and the combustion controller sections. Each section uses independently trained neural networks. The dioxyne prediction network uses incinerator sensor input and predicts the carbon monoxide (hence dioxyne) emission rate before the actual emission occurs. The combustion controller network uses input from the dioxyne prediction network as well as incinerator sensors, and outputs incinerator control values which will decrease the carbon monoxide emission.

For this paper, we will propose methods applying neural networks to construct the dioxyne prediction network. We will discuss the combustion controller network in future works.

IV. DIOXYNE PREDICTION NETWORK

For the dioxyne prediction network, we first consider the standard 3 layer feed forward neural network with BP (back propagation) training.

For the network input data, we use all of the sensor data except carbon monoxide concentration values, and the single output of the network is used to predict the correct carbon monoxide concentration.

For the network training we use the database of incinerator sensor data collected, and apply BP training based on the difference between predicted carbon monoxide concentration and the actual carbon monoxide concentration recorded for the.

As a preliminary experiment, we constructed a neural network taking all of the sensor values except carbon monoxide values as input data, and trained the network to output carbon monoxide values directly.

Figure 1 shows the training results of the preliminary experiment. From the results of the preliminary experiment, we found that the prediction accuracy is completely different between normal range carbon monoxide values, and high carbon monoxide values. The network learned to accurately predict normal range carbon monoxide values fairly quickly, but the same network failed to learn abnormal (high) range carbon monoxide values during the same training period. When network training was continued in order to increase the abnormal range carbon monoxide prediction, this time the accuracy of normal range carbon monoxide prediction deteriorated. This finding confirms our initial estimate that it would be difficult to train the neural network due to the complexity (if any) of the correlation between carbon monoxide concentration and each of the other sensor values.

For this reason, we decided to focus on detection of abnormally high carbon monoxide emission (>100ppm) as the preliminary goal of the dioxyne prediction network.

The network output was changed from direct carbon monoxide concentration prediction value, to binary output where 1 predicts high carbon monoxide concentration (>100ppm) and 0 predicts normal carbon monoxide concentration ($\leqq$ 100ppm).

As for the neural network input, we considered the possibility that the large number of input nodes increases the problem domain and complicates the classification, causing an adverse affect on the network training efficiency. With this assumption, we decided to minimize the number of input nodes in order to first achieve a workable learning curve and prediction accuracy.

As mentioned before, is can be noted that oxygen concentration, flapper angle and carbon monoxide concentration are related, from the similar changes seen sequential data. Based on this assumption, for the initial model we use only flapper angle and oxygen concentration data as neural network input. Further, we assume that flapper angle, oxygen concentration and carbon monoxide concentration each show a particular time delay in their relationship. For this reason, in order to predict the carbon monoxide value for a given instance, the flapper angle and oxygen values must take into account the time delay. Data at some fixed time frame previous to the given instance should be used as the input data. Recurrent network structures could be used to treat such time sequence data effectively, but for the initial model, we map sequential data of flapper angle and oxygen concentration to individual input nodes to the network. Specifically, 4 sequential data for both flapper and oxygen data, for a total of 8 input nodes were used for the initial network.

V. EXPERIMENT RESULTS

In order to confirm the effectiveness of the proposed dioxyne prediction network, we trained the proposed artificial neural network using BP and compared the prediction accuracy. A standard sigmoid function was used as the neuron's base synapse function. The number of neurons used in each layer was 9 input neurons (8 inputs and 1 fixed input), 9 hidden layer neurons, and 1 output neuron.

For the training data, 100 cases of normal range carbon monoxide data and 100 cases of abnormal (>100ppm) carbon monoxide data, for a total of 200 cases were randomly selected from the incinerator sensor database. For the untrained data used to plot the training curve of network accuracy, 100 cases of normal range carbon monoxide data and 100 cases of abnormal range (>100ppm) carbon monoxide data, for a total of 200 cases were randomly selected from the incinerator sensor database.

Figure 2 shows the change in output error for the untrained dataset of the proposed neural network. The output error for normal range carbon monoxide values, output error for abnormal range (>100ppm) carbon monoxide values, and total output error is graphed.

Figure 3 is the graph of prediction accuracy for the same training results as Figure 2. The prediction accuracy shown here is the rate the network correctly predicted either normal or abnormal output. Here, output < 0.5 for normal carbon monoxide cases and output > 0.5 for abnormal carbon monoxide cases were considered as correct prediction. The prediction accuracy for normal range carbon monoxide values, prediction accuracy for abnormal range (>100ppm) carbon monoxide values, and total prediction accuracy is graphed.

VI. CONCLUSION

The final prediction accuracy shown in Figure 3 was 0.82 for total prediction accuracy, 0.77 for normal range carbon monoxide values, and 0.88 for abnormal range carbon monoxide values. As was seen in the preliminary experiment, when the network is trained to increase the abnormal range output prediction, the normal range output prediction in turn decreased. But for this current proposed model the aim was to achieve workable prediction accuracy, and in this light we believe we achieved the goal. Further, as the original aim of the proposed dioxyne prediction network is to predict the occurrence of abnormal carbon monoxide emission (hence dioxyne emission), we believe it is acceptable to put priority over accuracy of abnormal range carbon monoxide output compared to accuracy of normal range carbon monoxide output.

For future works, we will consider methods to improve prediction accuracy, including the increase in the types of sensor input data, reevaluation of neural network structure (including recurrent network structure), as well as effect of using different base synapse functions for neurons.

REFERENCES

[1] Makoto Fujiyoshi, Ryutaro Fukushima, Mitiharu Masuya, Intelligent Control System for Fluidized Bed Incinerator, Japan Society for Fuzzy Theory, Proceedings of 18th Fuzzy System Symposium, pp.25-28, 2002

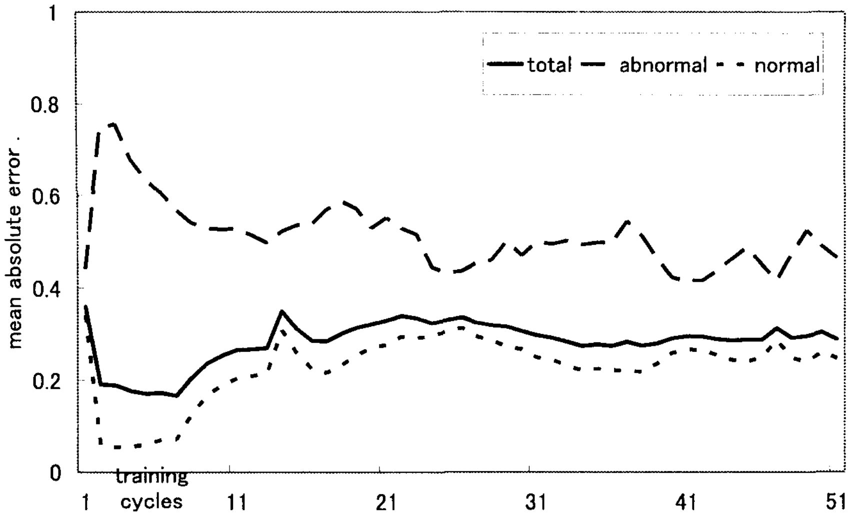

Figure 1. Preliminary experiment results of prediction error for untrained data

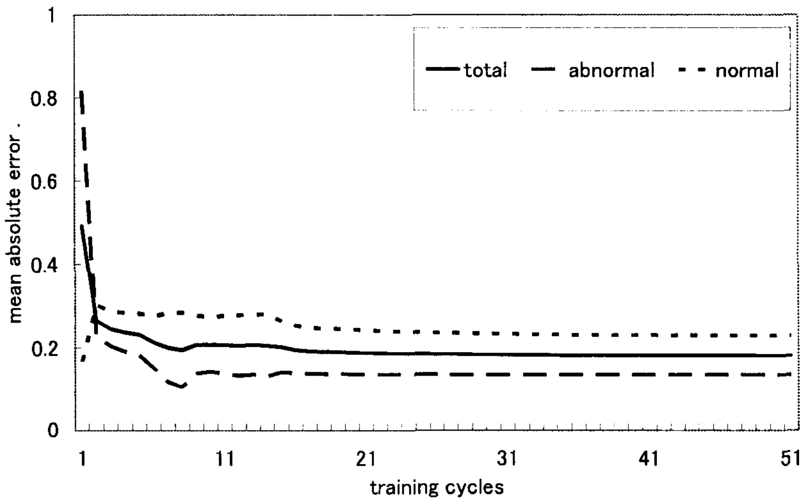

Figure 2. Prediction error of untrained data using proposed method

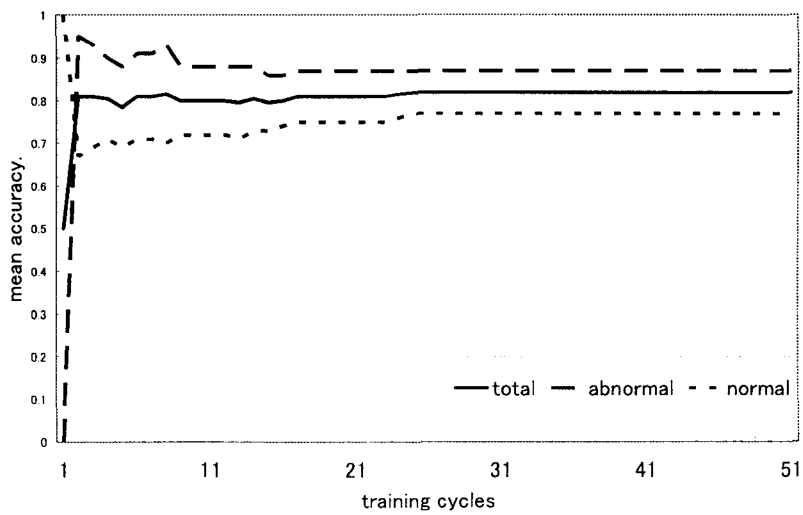

Figure 3. Prediction accuracy of untrained data using proposed method