AN ANALYSIS METHOD FOR OPERATIONS OF HOT WATER HEATERS BY ARTIFICIAL NEURAL NETWORKS

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Summary Authors tried to apply an Artificial Neural Network (ANN) to estimation of state of building systems. The systems used in this study were gas combustion water heaters. Empirical equations to estimate gas consumption from measureble properies such as exhaust gas temperature and electric current were obtained from experiments. Some operational modes, which were hot water supply, additional combustion to keep water temperature in bathtub, and anti-frozen heater for plumbing, were needed to be identified. Electric currents, temperature of supply water and exhaust gas had been measured as operational indices. ANN was applied to identify modes automatically using learning algorism. The modes were porperly identified and gas consumption was estimated in practical accuracy.

Keywords: domestic hot water, artificial neural network, energy.

INTRODUCTION

Building service systems are very complicated. It would be difficult to know how the systems are operated, even if reasonable measurements were conducted. Furthermore, not all physical properties could be measured. The methods to clarify the system status from limited measurement data are needed. The purpose of this study is to establish a method to identify building service system status from limited information. As authors had been involved energy consumption measurement of a residential building for seniors, estimation of gas consumption for domestic hot water supply had been needed. In the analysis of measurements, estimation of gas consumption from few kinds of measured values and an identification of operational modes of gas combustion heaters from limited data were required.

In Japan, domestic hot water supply usually done by a gas combustion water heater, and cooking is done by gas ovens. To clarify the structure of energy consumption, energy consumption of hot water supply and cooking should be divided, because gas consumption is measured by one gas meter. Since it is very difficult to install gas flow meters to both cooking gas lines and hot water supply gas lines, authors conducted experiments to estimate gas consumption from several measurable properties such as temperature of exhaust gas and electrical current. Artificial Neural Networks (ANN) was applied to identify operational modes because some water heaters had several modes. Due to ANN's learning algorism, once network had been established, identification could be conducted automatically. It was expected that ANN was able to identify the operation modes for hot water heaters.

METHODS

Authors conducted expriments to estimate gas consumption from limited number of physical properties. The gas consumption was measured in given condition, and relations among gas consumption, exhause gas temperature, and electiric current were derived. Figure 1 shows schmatic a diagram of exprimental setup. The hot water heater was an ordinaly used in Japanse houses, whose nominal capacity was 27.9 kW.

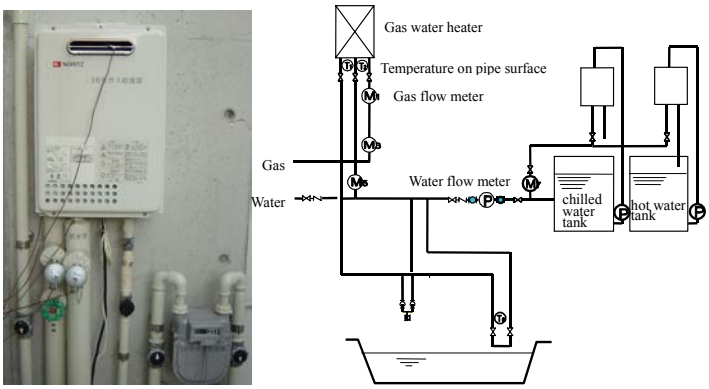


Figure 1. Schematic diagram of experimental setup

The supply water temperature to the gas heater was adjusted by mixinig chilled water and hot water. Gas flow rate and water flow rate were measured by flow meter. Supply water temperature and hot water temperature were measured on the surface of each pipes. Exhaust gas temperature was measured at outlet. Electric current was measured.

The exprimental condition of supply hot water temperature was set to 45°C, 40°C and 37°C. The phases of expriment were settled, considering usage of hotwater. For hot water supply for bath tub, 150 litters of hot water was supplied. 5 minutes for shower operation and 4 and 7 minutes for dish washing were duration of experiments.

From results, we found correlations among gas flow rate, supply water temperature, hot water temperature, exhaust gas temperature and electic current. Equation (1) between gas consumption and 4 varibles was derived. The coefficent of determination, R^2 was not very high. At the beginning of experiments, the gas heater was in unstable conditions. The proportion of these unstable operation was larger for expriments with short durations. Authors had not dismissed these results, because shorter operations occured in actural usages.

$$f_g^* = 1.191 t_e^* + 0.570 t_{ws}^* - 0.989 t_{hs}^* + 0.211 I^* - 0.186 \qquad (1)$$
$$R^2 = 0.810$$

On the actual measurement, all variables above might not be measured, for such reasons as shortage of data logger capacity or space for sensors. The correlation with 2 variables, which were exhauset temperature and electric current, was derived as shown in Equation (2). The coeffcient of correlation became smaller than Equation (1). The variable t_e* was siginificant at 1 % and I* was significant at 5 %.

$$f_g^* = 0.857 t_e^* + 0.323 I^* - 0.391 \qquad (2)$$
$$R^2 = 0.750$$

IDENDIFCATION OF OPRATION MODES

Some hot water heaters used in this study had several operation modes. Figure 2 shows diagram of water heater and result of a measurement.

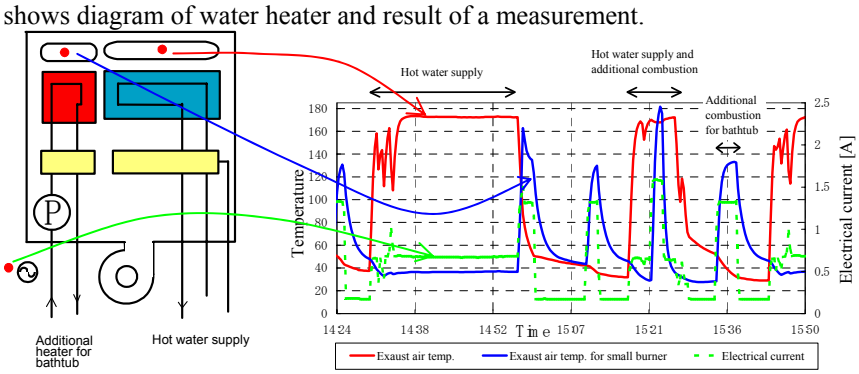
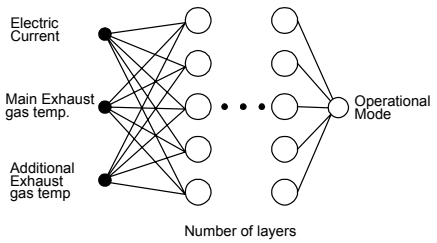


Figure 2. The diagram of heater and operational modes

The heater had 2 burners, which were main burner for hot water supply and additional heater for a bathtub. According to conditions, the heater was operated automatically. The modes were a hot water supply mode, an additional combustion for bathtub, anti-freeze electric heart operation, and both hot water supply and additional combustion. These modes resulted in temperature and electric current variation. Equation (1) and (2) could only be applied to hot water supply mode.

If gas consumption was calculated for other modes, the results were not trustful. These modes could be identified by considering operation of the heater. For hot water supply mode, main burner was operated so that only exhaust gas temperature of main burner rose. For additional combustion for bathtub, additional burner was in operation. No burners were in operation for anti-freeze electric heater operation. Since additional combustion and main combustion sometimes occurred simultaneously, consequently identification became complicated.

Artificial Neural Network was adopted to automate identification process. Inputs were main and additional gas exhaust temperature, and electric current. Figure 3 shows the configuration of artificial neural network. Each mode was appointed to normalized value since sigmoid transfer function was applied. The number of elements and layers of network was decided by trial and error.



Modes	Value
Hot water supply and additional combustion	1
Hot water supply	0.5
Addintional combustion	0
Anti-freeze heater	-0.5
Without operation	-1

Figure 3. Configuration of artificial neural network

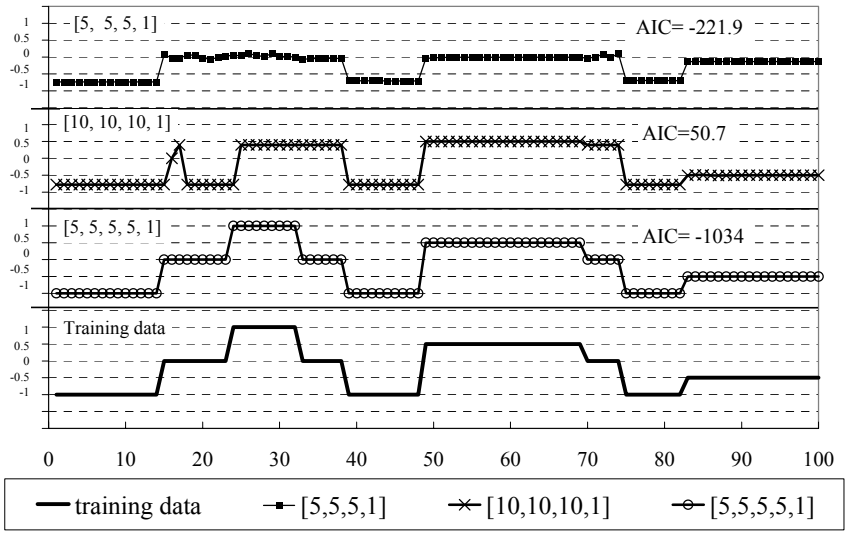


Figure 4 A result of training for 100 data

MATLAB Neural network tool box was used for constructing network and training. Before training, a training data of inputs and outputs was determined. We chose a set of operational data considered to contain each operational modes, and identified each mode by observing data. Several configurations of network were tried to find optimum one.

Figure 4 shows the result of training. The network with 5 nodes and 5 layers showed good agreement with training data. AIC value in the figure was Akaike information criterion shown in Equation (3), which was a performance measure for ANN. The AIC shows trade off between training performance and network size. It rewards a network with low Mean Square Error (MSE) but penalizes networks with a large number of weights. Thus the network with 10 nodes, [10, 10, 10, 1] had large value of K, and resulted in larger number of AIC. Network which had 5 nodes and 5 layers showed minimum AIC

$$\mathrm{AIC}(k) = N \ln(MSE) + 2K \qquad (3)$$

The network might be too much optimized to specific training data if training data was not large enough. Therefore we trained the network with larger data, which contained 200 sets. AIC value became –812.34 for the network. We considered that the network had reasonable size and accuracy.

Once operation modes were estimated, the gas consumption could be calculated for each mode. For the hot water supply mode, correlation derived from experiments could be adopted. In the measurements conducted in this paper, since only exhaust gas temperature and electric current were measured, Equation (2) was adopted. For additional combustion, gas consumption was constant value of 11.5kW from manufacturer's data. The gas consumption from Equation (2) and the constant value were added for the hot water supply and additional combustion mode.

The estimation of gas consumption for 2 days, which consisted of 3241 sets of data, was conducted using the network. The estimation by the network was 9.10m^3 and the gas consumption of training data was 8.17 m^3. The network estimated 11.4% higher value. Table 1 shows the correspondence with estimated result for each mode. The correspondence for the modes of additional combustion and without operation was low.

Figure 5 shows a case where difference between the estimated data and training data was significant. The lower part of figure demonstrates comparison between real and estimated mode. Although an additional combustion occurred form 13:01 to 13:04, the network estimated the mode to be without operation. At 13:19, although the gas heater stopped, the network estimated that hot water supply and additional combustion operation continued. These inadequate estimations were caused by lack of certain combinations in training data. The training data didn't contain combinations of data after gas heater stopped. Since exhaust gas outlet was still warm, the network mistook the temperature for hot water supply.

Table 1 Correspondence between estimation and actual modes.

Modes	Appear -ance	Correct Estimation	Rate	Correct Estimation (Modified)	Rate
Hot water supply and additional combustion	45	29	64.4 %	2	4.4 %
Hot water supply	834	716	85.9 %	733	87.9 %
Addintional combustion	234	70	29.9 %	176	75.2 %
Anti-freeze heater	60	55	91.7 %	31	51.7 %
Without operation	2068	895	43.3 %	1962	94.8 %
Total	3241	1765	54.5 %	2904	89.6 %

Therefore, we modified the training data adding 100 more combinations that mainly consisted of without operation immediately after the heater stopped. The correspondence of estimation was shown in Table 1 and Figure 5. The correspondence rate for whole period was improved from 54.5 % to 89.6 %. Especially, correspondence in without operation and additional combustion was noticeably improved. After training, the difference between training data and estimation reduced to 2.9 %. However, correspondence of hot water supply and additional combustion became very low. We admitted this disagreement, since the appearance of this mode was smallest.

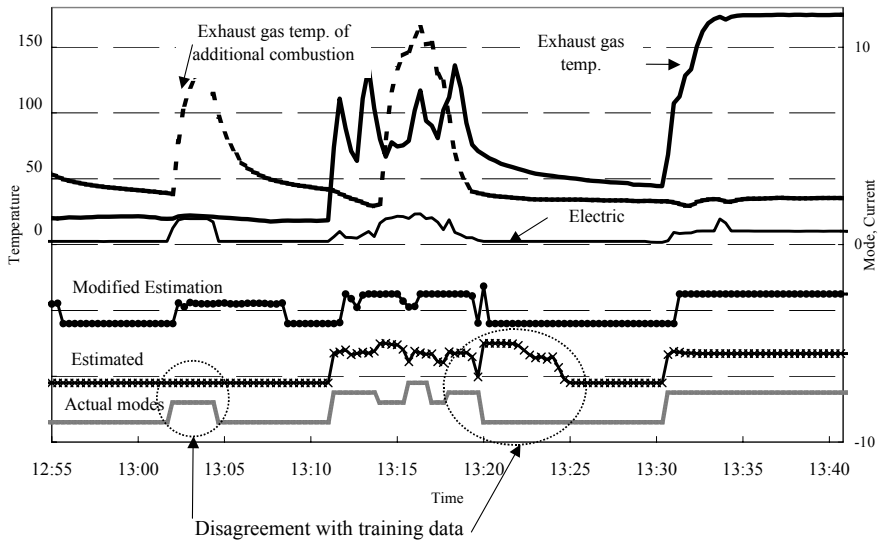


Figure 5. An example of disagreement with training data

THE ESTIMATION OF GAS COMSUPTION

The network trained above was used to estimate gas consumption of a residential building. The building was residents for 50 seniors and located in Nagoya city. There were 10 gas combustion heaters and a boiler for main bath. The 3 of 10 gas combustion heaters had 2 burners and were needed identification of operation modes. Measurements of temperature and electric current had been conducted form 12th to 16th of April 2003. Table 1 shows the result of estimation using ANN. A ratio of hot water supply to whole building gas consumption was showed in Figure 8. The structure of gas consumption would be investigated by measurement for certain period.

Table 2. Estimated gas consumption of each heater

No. of Heaters	Gas consumption [m^3]	No. of Heaters	Gas consumption [m^3]
No. 1	6.3	No. 7	12.2
No. 2	6.9	No. 8	8.3
No. 3	8.0	No. 9	8.0
No. 4	31.7	No. 10	10.0
No. 5	5.8	Boiler	2.0
No. 6	5.2	Total	104.3
	indicates the heaters with estimation		

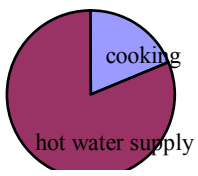


Figure 6. Proportion of gas consumption

DISCUSSION

In the building service field, a status of building system should be estimated form observed data. Authors consider that methodologies for estimation would be inevitable, and tried to estimate gas consumption for domestic hot water heater. The measure to estimate gas consumption form limited measurable data was examined. Furthermore, ANN was adopted to identify the operation modes.

The empirical correlations were obtained form experiments. The coefficients of determination of correlations were around 0.8, which were not very high value. The more experiments considering conditions would be needed to increase accuracy. Furthermore, consideration from heat exchange model for burners should be effective in addition to statistical methods.

Authors considered that the ANN, that was able to estimate the modes of operation accurately, could be configured. In this study, ANN with 5 nodes and 5 layers had minimum AIC value, and was concluded to be an appropriate network. However, when estimation was conducted for the actual application, it was not done correctly if the training data was inadequate. It was careful to select training data for all modes. Therefore, one should consider which mode was important for specific analysis.

The ANN could be trained and compose the model without considering system physical characteristics. These aspects would be advantages for large building systems, which were difficult to compose physical models, and automatic diagnosis system. However, accuracy of network depends on how the training data is chosen. System status cannot be identified correctly, if a training data is deviated despite of size of the data. Authors treated domestic gas heaters in this study, and would like to develop method for building HAVC systems.

NOMENCLATURE

f_g^*	normalized gas flow rate; $f_g^* = f_g / f_{g,rated}$
t_e^*	normalized exhaust gas temperature; $t_e^* = (t_e - t_{e,minmum})/(t_{e,maximun} - t_{e,minmum})$
I^*	normalized electric current; $I^* = I / I_{rated}$
t_{ws}^*	normalized supply water temperature; $t_{ws}^* = (t_{ws} - t_{ws,minmum})/(t_{hs,maximun} - t_{hs,minmum})$
t_{hs}^*	normalize hot water supply temperature $t_{hs}^* = (t_{hs} - t_{ws,minmum})/(t_{hs,maximun} - t_{hs,minmum})$
MSE	Mean Square Error between training data and estimated results
K	Number of free parameter of the network

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