Intelligent Approaches for Intrusive Monitoring of Appliance Loads

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***Abstract*—Power utilities must understand how customers use their products and monitoring/survey analysis of customer usage patterns is the best way to understand how customers use electricity. This is essential to formulate any long term planning, forecasting or marketing strategy. However, only customer's service level loads (total loads) are available. As the collection and analysis of customer usage data is very costly and time consuming, most power utilities do not allocate the necessary resources required to properly address this issue. That's why such an important necessity has been left unattended. If we could decompose the service level loads into end-use load profiles, then we are able to analyze them. In this study, a multi-agent system is applied to analyze the residential customer usage patterns in a cost-effective way. For this study, a power utility has recorded the service level load of residential customers in 15-minute intervals over 3 months. A residential survey collected by the same utility is also used. The seven-channel end-use meters are installed as a part of a pilot program to study the validity of end-use load research. In this research, every agent represents an appliance. Also, an artificial neural network (ANN) is assigned for each agent. Back-propagation (BP) learning algorithm is used to learn about the environment and communication among agents. We analyzed the manner in which the BP learning algorithm can be used in such a system. We also discovered several problems discussed in the paper in applying BP learning to multi-agent systems. Here for the sake of simplicity, only one household is taken into account for simulation. The simulation shows that the present study can provide detail information that currently does not exist. This project is currently being implemented.**

***Index Terms*—Artificial neural network, back-propagation learning, decomposition, end-use load profiles, monitoring, multi-agent system.**

I. Introduction

THE PROGRAM outlined in this paper examines a method of analyzing customer usage patterns in a cost-effective way. The proposed work analyzes hourly load data using ANNs, which are assigned for agents. For this study, we used the data provided by a power utility that has fortunately implemented a statistically valid load research program, which records the service level load of customers in 15-minute intervals. Also, the Rates Department of the same power utility has been granted a project to conduct an end-use load research program in conjunction with the existing service level-metering program. Therefore 28 seven-channel end-use meters were installed as a part of a pilot program in 28 households to study the validity of end-use load research.

This end-use study provides detail information that currently does not exist. But there are two major problems:

- The sample size of 28 households is very small,
- The equipment is very expensive. Therefore, it was decided to apply a methodology to solve this problem without incurring the expense of purchasing additional end-use monitoring equipment.

The estimation of the demand curve of appliances, as a part of planning and operation of distribution systems has already been approached using different models: multivariate time series, structural linear regression [1], neuro-fuzzy approach [2], and stochastic processes [3]. All of these approaches require sampling and it is a very difficult task to monitor appliances in households. Expensive hardware that records turn on and turn off transients has also been used to identify appliance cycles [4]. In recent years, ANN has shown promising performance in many areas of power systems particularly load forecasting [5]. However, there is little work on the decomposition of end-use profiles from service level metering [6]. Moreover, there is also little work on the application of multi-agent for the problem mentioned above.

The authors have previously published a paper [7], which considers a stand-alone ANN applied to the same problem. However, as all appliances are put together in a stand-alone ANN, their individual actions and/or communication are unknown. In this study, we have considered a system, which takes into account each appliance separately (multi-agent system). It should be noted that multi-agent systems are mainly used for the distributed processing in software engineering, robotics and telecommunication [8]-[10].

The structure of this paper is as follows. Section II presents the outline of a multi-agent system together with its application toward the estimation of end-use appliance from a household total load curve. The design of a multi-agent system using the ANN learning behavior is described in Section III. Then, Section IV discusses the design of an appliance-ANN for the end-use program. Section V revisits some of the contributions made in this paper. The paper concludes in Section VI.

II. Multi-agent System

There are several agents in a multi-agent system and they model each other's goals and actions. In a fully general multi-agent scenario, there may be direct interaction among agents (communication).

Multi-agent systems, a sub-field of artificial intelligence, study the interactions of computational agents. These agents can represent real world parties, and they can have

Manuscript received March 6, 2002; revised November 26, 2002.

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Publisher Item Identifier S 1682-0053(03)0142

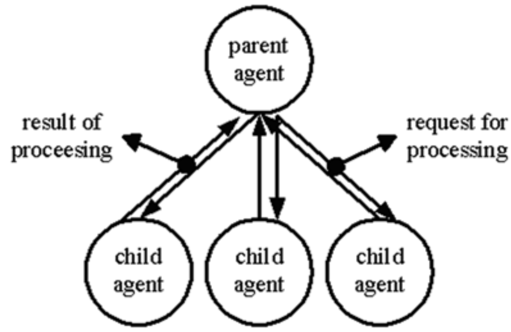


Fig. 1. A multi-agent system.

different preference structures. A key research goal is to design open distributed systems in a principled way that leads to globally desirable outcomes even though every participating agent only considers its own good and may act individually. Since multiple agents do the processing in any system, the system divides a given problem into parts and asks the agents to solve that particular part of the problem. This is more useful than a single object (agent) tackling the whole task with a centralized agent. From a programming perspective, the modularity of multi-agent systems can lead to simpler programming as well. In a multi-agent system, an agent called "parent agent" can identify subtasks and assign control of those subtasks to different agents (child agents). The child agents then return the results of processing to the parent agent as shown in Fig. 1.

The features of the multi-agent systems and common properties that make them different from conventional methodologies are: (a) agents are autonomous, that is they act on behalf of the user, (b) agents contain some level of intelligence, from fixed rules to learning engines that allow them to adapt to changes in the environment, (c) agents don't only act reactively, but sometimes also proactively, (d) agents have social ability, that is they communicate with the user, the system, and other agents as required, (e)agents may also cooperate with other agents to carry out more complex tasks than they themselves can handle.

Here, the idea of applying a multi-agent system to the estimation of load profiles of end-use appliances of households is presented in the next section.

III. Design of a Multi-agent System

In this study, the main task is to estimate the load profiles of end-use appliances from the total loads. We can assign one agent for each appliance in the targeted household (Fig. 2). This agent is called "Appliance-Agent". Another agent requests the child agents to process a defined task and receives the processing results from them and is called "Main-Agent". They are explained as follows:

A. Main-Agent

The Main-Agent, which is the parent agent in Fig. 1, does the following processing. First it receives the data (inputs of Appliance-ANN) from outside and sends them to the Appliance-Agent to process a shared task. Next, after receiving the processing results from the Appliance-Agent, communication media is needed to act as interface between the outside environment and the Main-Agent.

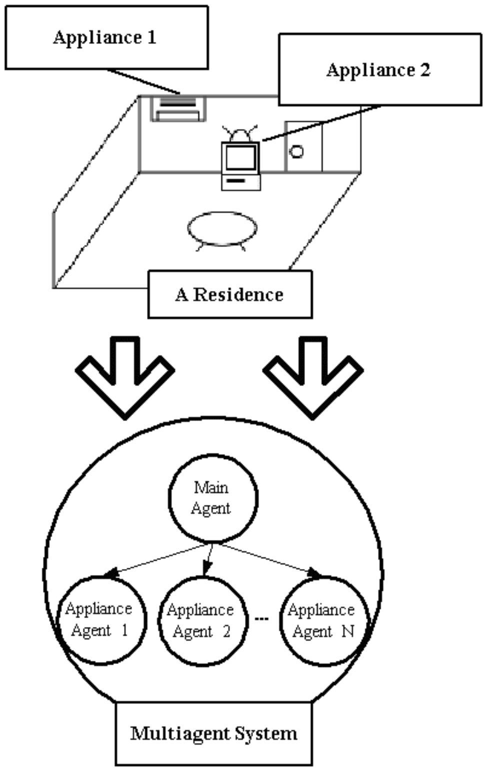


Fig. 2. A typical multi-agent system employed for estimation of appliances load profiles.

B. Appliance-Agent

The structure of an Appliance-Agent is shown in Fig. 3. When time-of-the-day, total service level metering (total load), temperature and so forth are selected as inputs to the Appliance-Agent, the load profiles of an end-use appliance become the output of the Appliance-Agent.

With the help of an ANN, called as "Appliance-ANN", the relationship between input and output can be recognized.

IV. Design of an Appliance-ANN for the End-use Program

In this section, necessary steps for designing the Appliance-ANN are presented. Basically, we should choose a set of input factors, which we think will be useful in estimation of end-use load profiles (Watt usage) from the service level loads.

A. Determination of Inputs and Output

1) Output Factor

The output factor of each Appliance-ANN was decided to be the hourly end use profiles. Our basic goal is to find about the load profiles of major appliances. In this case, 1 neuron was assigned as the output of each Appliance-ANN. It should be noted that 7 Appliance-ANNs (7 different appliances) are present in our multi-agent system. These appliances are selected based on their annual usage. They are:

- Window Air conditioner
- Furnaces with 1 speed fan
- Furnaces with 2 speed fan
- Electric Water Heaters

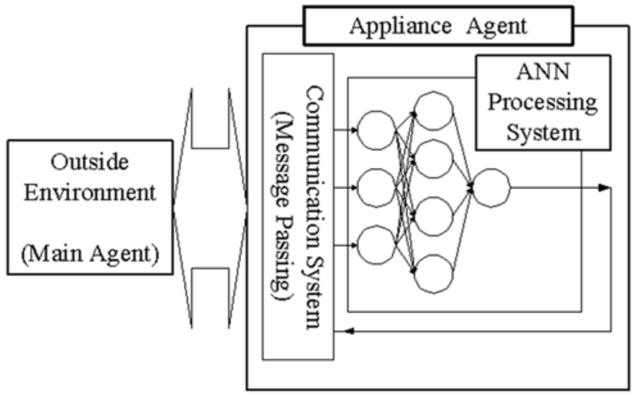


Fig. 3. The structure of an Appliance-Agent.

- Refrigerators
- Microwave ovens
- Dehumidifiers

2) *Input Factors*

The most important and hardest part is the determination of input factors. It is hard, because we are trying to take some information (Watt usage of 7 appliances) out of an hourly service level load. Usually the opposite way is rather easy. In order to have a successful decomposition/estimation, other related information also should be added to the above mentioned *service level load*.

It should be noted that the data for this study was collected from a prefecture where there are extremes of temperature. It is cold in winter and hot in summer. The electric heating load is therefore significant at one part of the year, and the air-conditioning load is significant at another part of the year. It is then hypothesized that the *temperature* will govern the amount of change in peak load from one week to the next. This is true because most utilities have large components of weather-sensitive load, such as those due to space heating, air conditioning, and agricultural irrigation. (These were chosen for their apparent relationship to changes in the daily loads and for the availability of reliable predictions of the external temperature.)

In addition to weather condition parameters some principal time factors, *hour-of-the-day, day-of-the-week* (weekdays and weekends), *month-of-the-year* play an important role in influencing load patterns. *National holidays* including Saturdays, Sundays cause discontinuities in the automatic operation. Therefore, these factors will also be added to the network for further training and testing.

3) *Number of Hidden Neurons*

Hidden layer neurons in this study are selected as the following manner:

The selection of hidden layer neurons is probably more art than science. It can vary widely according to the application and bears a relationship to the number of statistically significant factors that exist in the input data. For this study, the number of neurons in the hidden layer was varied from 20 to 50. We found that if we select too few hidden neurons, the network would not train at all. And if we select just barely enough, the network may train but it might not be robust in the face of noisy data, or it would not recognize patterns that it has not seen before. Too many neurons, in addition to taking forever to train, tend to create a network that has memorized everything and again, does not recognize new patterns very well. In other words, it does not generalize well.

The experiment using various numbers of hidden neurons is necessary since, as far as the authors are aware, there is no known technique to determine the exact number of hidden neurons beforehand which leads to an optimal solution. Therefore, the empirical approach was used this experiment. In other words, a trial and error scheme has been adapted to determine the appropriate number of hidden neurons. It started with 20 neurons and then gradually increased the numbers and calculated training error. Training is carried out until the lowest training error is reached. As shown in Table I, for this study the optimized numbers of hidden neurons vary form 20 to 50 for different networks and different employed inputs.

After selecting the number of hidden neurons, the neurons function is tuned as follows:

Once the outputs of all hidden layer neurons have been calculated, the net input to each output layer neurons is calculated in an analogous manner, as described by (1). Similarly, the output of each output layer neurons is calculated as described by (2),

$$i = \sum_j w_j o_j \tag{1}$$

$$o = \frac{1}{1 + e^{-\frac{i}{T}}} \tag{2}$$

where i , o , w_j and T represent the input, output, j -th weight, and temperature of sigmoid function, respectively.

The set of calculations the results in obtaining the output state of the network (which is simply the set of the output states of all of the output neurons) is carried out in exactly the same way during the training phase as during the testing/running phase. The test/run operational mode just involves presenting an input set to the input neurons and calculating the resulting output state in one forward pass.

B. Data Collection

Measurement is carried out under the condition mentioned above. In the research program implemented by the power utility, the service level load of residential customers has been recorded in 15-minute intervals. However, since other factors have hourly data, we have converted the 15-minute data into hourly data. The entire length of the data is recorded over a 3 months period (January 1 to March 31 of 1993). Therefore, we trained the Appliance-ANN with 3 months of data. It should be noted that the last week of the data is not included in training and only used for testing the trained agent. This is called "unseen data".

The reason why only 3 months of data has been collected is because the validity of ANN application must be seen for each agent as fast as possible. The second reason is to have a reasonable and fast learning by a small data set. This is because the training of ANN always takes time, and therefore huge data sets may slow down the training time. As the length of training data is very limited,

TABLE I
OPTIMAL PARAMETERS OF THE APPLIANCE-ANN.

Appliances	Input Neurons	Hidden Neurons	Output Neuron	Learning Rate	Momentum	Inverse of Temperature
Window Air	11	16	1	1.0	0.6	0.2
Furnace with 1 speed fan	11	36	1	0.9	0.9	0.1
Refrigerator	11	42	1	0.2	0.9	0.1
Microwave	11	32	1	0.2	0.9	1.4
Electric Water Heater	11	40	1	0.2	0.9	0.1
Dehumidifier	11	40	1	0.2	0.9	0.3
Furnace with 2 speed fan	11	10	1	0.5	0.9	0.5

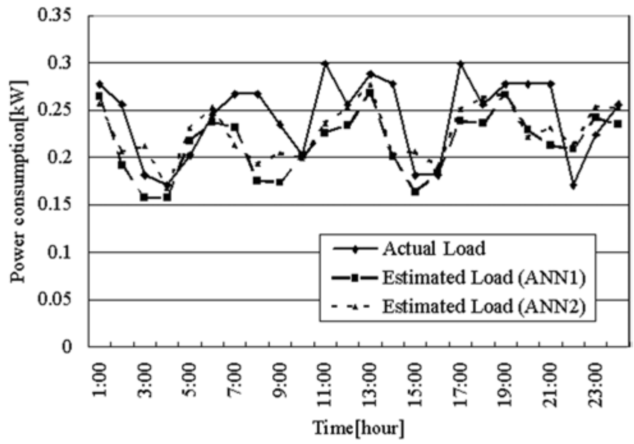


Fig. 4. Estimation of the load profiles of a Furnace with 1 speed fan (March 15).

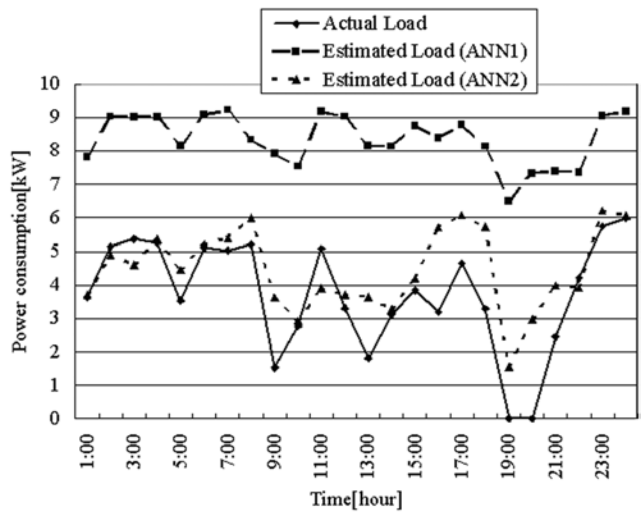


Fig. 5. Estimation of the load profiles of an Electric water heater (January 26).

training time. As the length of training data is very limited, a careful study on selection of appropriate input factors was carried out. For this purpose, we carefully checked the correlations between the output and the inputs and selected the most related inputs.

V. SIMULATION RESULTS

A. Optimal Structure of the Appliance-ANN

In order to find the best model suited to the problem mentioned above, there is no way except trying several configurations and select the optimal one among them. The optimal network is the one that has lowest error and reasonable learning time. Here, three different 3-layer networks were tried. They are described as the following Appliance-ANN1, Appliance-ANN2, and Appliance-ANN3.

We have found that when we use a binary number for the number of hour-of-day neurons, the training performance changes significantly. This is because the number of inputs is reduced and less noise is injected into the network. We also found that at least 2000 Epochs are necessary for the successful learning of the Appliance-ANN. The results of various simulations on different appliances are shown in Figs. 4 and 5. Here, the number of hidden neurons, referred to the rule of thumb, is set to 16. In Figs. 4 and 5, the ANN which uses 24 neurons for the hour-of-day is called "Apliance-ANN1" and the ANN which uses 5-digits of binary code for the hour-of-day is called "Appliance-ANN2".

Appliance-ANN1

Number of Input Neurons: 29
-Hour-of-day: 24
-Day-of-week: 3 (in binary)
-Temperature: 1
-Service level load: 1
Number of Hidden Neurons: 16
Number of Output Neuron: 1
Learning rate 0.4
Momentum: 0.9

Appliance-ANN2

Number of Input Neurons: 10
-Hour-of-day: 5 (in binary)
-Day-of-week: 3 (in binary)
-Temperature: 1
-Service level load: 1
Number of Hidden Neurons: 16
Number of Output Neuron: 1
Learning rate: 0.4
Momentum: 0.9

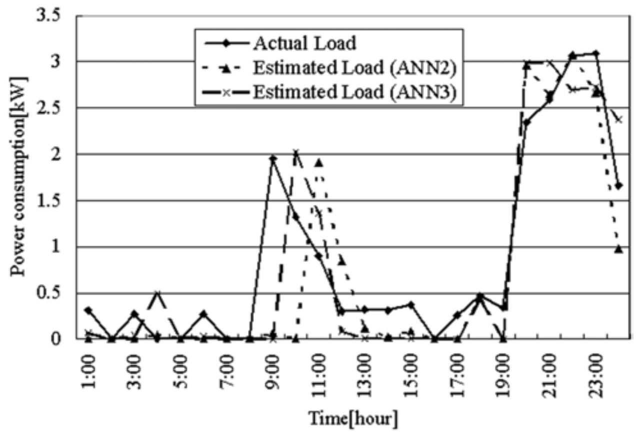


Fig. 6. Estimation of the load profiles of a Refrigerator (March 20).

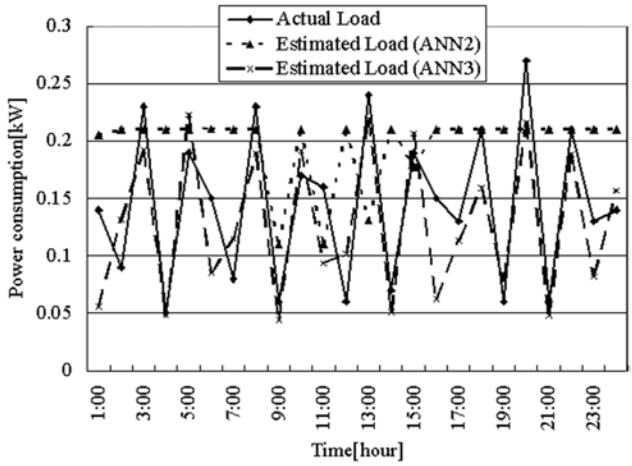


Fig. 7. Estimation of the load profiles of a Dehumidifier (January 20).

TABLE II
ESTIMATION EVALUATION OF ANN1 AND ANN2 IN FIG. 4

	ANN1	ANN2
Mean absolute error [kW]	1.85×10^{-3}	1.46×10^{-3}

TABLE III
ESTIMATION EVALUATION OF ANN1 AND ANN2 IN FIG. 5

	ANN1	ANN2
Mean absolute error [kW]	22.7	1.67

The results that compare Appliance-ANN1 with Appliance-ANN2 (Figs. 4 and 5) are shown in Tables II and III. These tables show that the learning error of Appliance-ANN2 is smaller than error of Appliance-ANN1.

Furthermore, after many simulations using different combination of inputs, we found that by adding the past hour load profile of the end-use appliance, more efficient training is gained. Therefore we added one additional neuron to the network. This ANN is called “Appliance-ANN3”. The results of learning using the Appliance-ANN3 are shown in Figs. 6 and 7, respectively.

<u>*Appliance-ANN3*</u>

Number of Input Neurons: 11
- -Hour-of-day: 5 (in binary)
- -Day-of-week: 3 (in binary)
- -Temperature: 1
- -Service level load: 1
- -Load profile of the past hour: 1

Number of Hidden Neurons: 16
Number of Output Neuron: 1
Learning rate: 0.4
Momentum: 0.9

The results that compare the Appliance-ANN2 with the Appliance-ANN3 (Figs. 6 and 7) are shown in Tables IV and V. From Figs. 6 and 7, it is obvious that Appliance-ANN3 is capable of learning the load profiles of appliances better than Appliance-ANN2. Therefore, we decided on Appliance-ANN3 (Fig. 8) as optimal structure of Appliance-ANN.

TABLE IV
ESTIMATION EVALUATION OF ANN1 AND ANN2 IN FIG. 6

	ANN2	ANN3
Mean absolute error [kW]	3.45×10^{-1}	2.84×10^{-1}

TABLE V
ESTIMATION EVALUATION OF ANN1 AND ANN2 IN FIG. 7

	ANN2	ANN3
Mean absolute error [kW]	8.23×10^{-3}	1.81×10^{-3}

B. Optimization of Parameters of Appliance-ANN

During the simulations, first, we fixed the learning rate, momentum, and temperature of sigmoid function, and then changed the number of hidden neurons from 20 to 50 until we obtained an optimal value. Here, the meaning of optimal value is the learning, which projects estimation with least error. Second, we changed the inverse of temperature of sigmoid function from 0.1 to 1.0 until we obtained the optimal value. It should be noted that in this stage the learning rate and momentum are kept fix and the number of hidden neurons is set to the optimal value, which was determined from the previous stage. Third, in a similar manner, we fixed the number of hidden neurons and temperature of sigmoid function to their optimal values, and then changed the learning parameters in the order of learning rate, momentum, respectively, from 0.1 to 1.0 until we obtained their optimal values. The obtained optimal parameters are shown in Table I.

C. Estimation Results

We trained 7 Appliance-ANNs 50000 Epochs after setting it as the optimal parameters. The estimated result is shown in Table VI. Also the two examples are shown in Figs. 9 and 10. The decomposition load profiles of 7 different appliances from the given service level load of a household is shown in Fig. 11. Furthermore, validation/effectiveness of the proposed method (multi-agent system: MAS) is verified through some comparisons with previous work (stand-alone ANN) [7]. The comparison results are shown in Figs. 12 to 14, and Table VI, respectively. In these comparisons, better performance is obtained by the proposed multi-agent system.

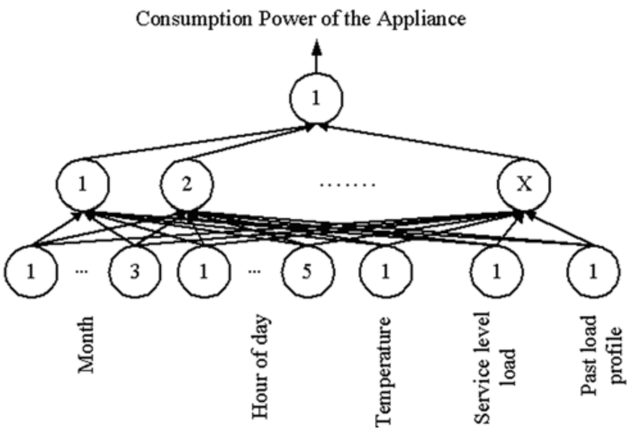


Fig. 8. Optimal structure of designed Appliance-ANN3.

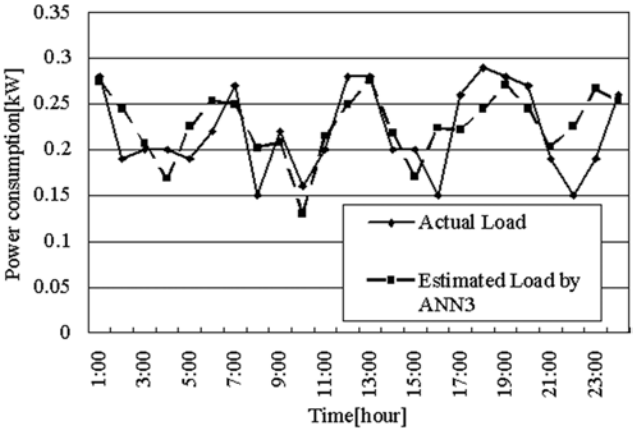


Fig. 9. Estimation of the load profiles of a Furnace with 1 speed fan (March 31).

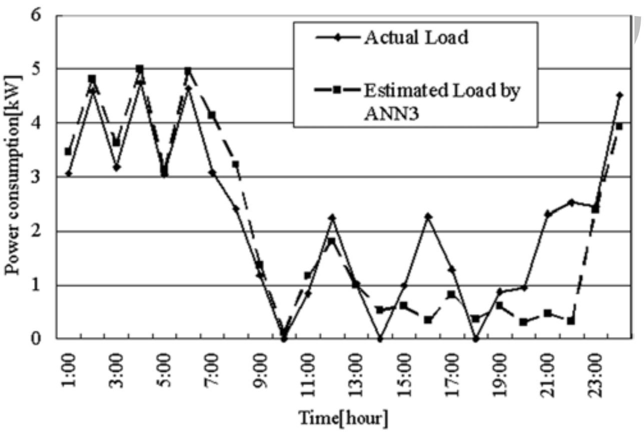


Fig. 10. Estimation of the load profiles of an Electric water heater (March 31).

Here, when service level load changes, it affects the way Appliance-ANN acts. The example of Electric water heater is shown in Fig. 15. This figure shows that the power consumption of Electric water heater is changing with the change of the service level load (refer to Fig. 15(a) and 15(b)).

Next, in order to estimate the load patterns of used appliances from the service level load, when the configuration is changed, we removed one and two appliances from the example sets and done some simulations. Figs. 16 (a) and 16 (b) show the results of estimation after removing Microwave, and Microwave and Furnace with 2 speed fan. Although the examples sets are changed, the estimation ability of our method has still kept

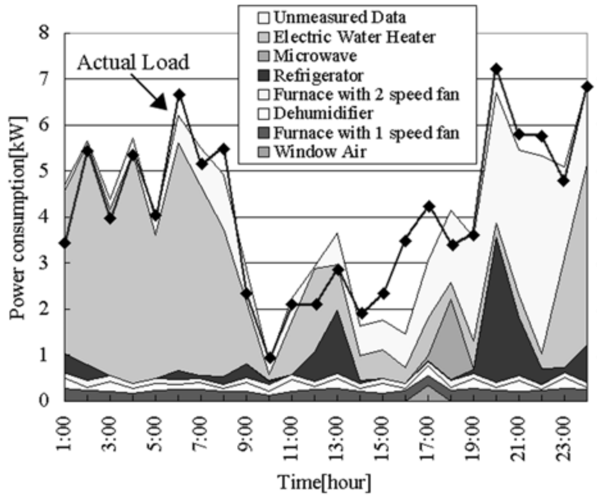


Fig. 11. Decomposition of the load profiles of 7 appliances from the hourly service level load.

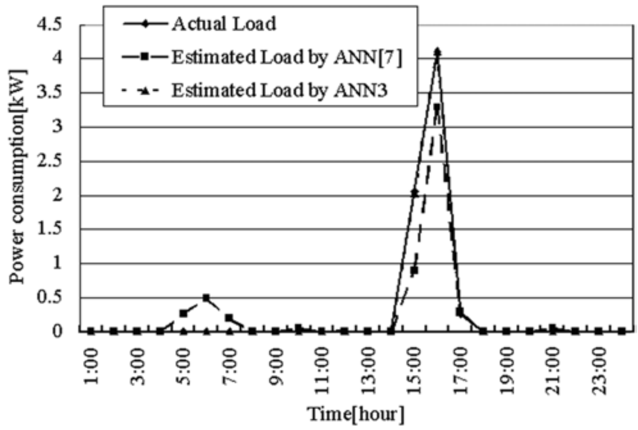


Fig. 12. Comparison of estimation of a Window Air (February 12) done by reference [7] and our proposed multi-agent system, MAS.

TABLE VI
ESTIMATION EVALUATION OF ANN3 IN FIGS. 9, 10, 12-14

Appliances	Mean absolute error [kW]
Window Air	1.25×10^{-1}
Furnace with 1 speed fan	2.94×10^{-2}
Refrigerator	5.35×10^{-1}
Microwave	1.09×10^{-1}
Electric Water Heater	8.01×10^{-1}
Dehumidifier	8.87×10^{-2}
Furnace with 2 speed fan	1.21×10^{-2}

within a reasonable level. However, when the configuration of the system under study changes a lot, it is needed to do re-forecasting to cope with proper appliances decomposition estimation.

Moreover, as a feature of our proposed MAS method, the process of re-forecasting is rather easy and does not need a lot of effects from the system on the study.

VI. CONCLUSIONS

In this study, a multi-agent system is applied for monitoring the load profiles of household appliances from a site that only has an hourly service level metering.

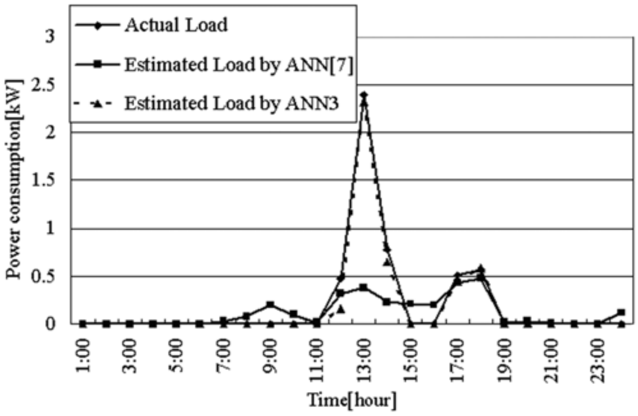


Fig. 13. Comparison of estimation of a Microwave (February 10) done by reference [7] and our proposed multi-agent system, MAS.

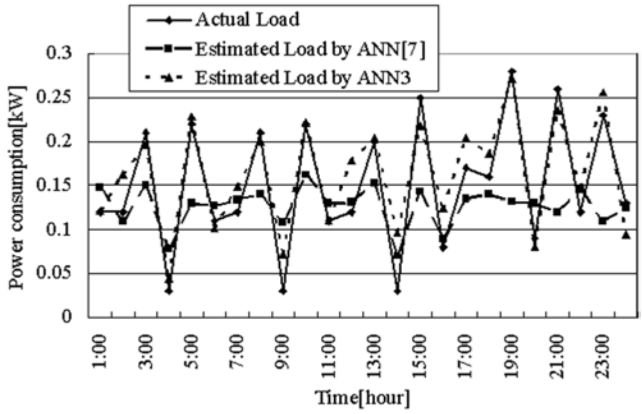
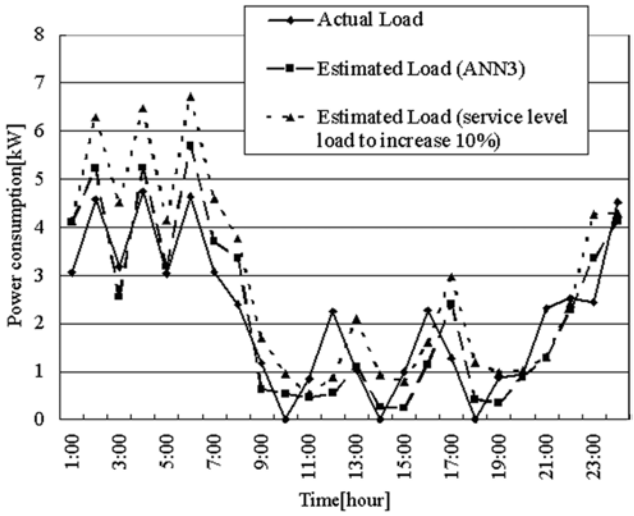
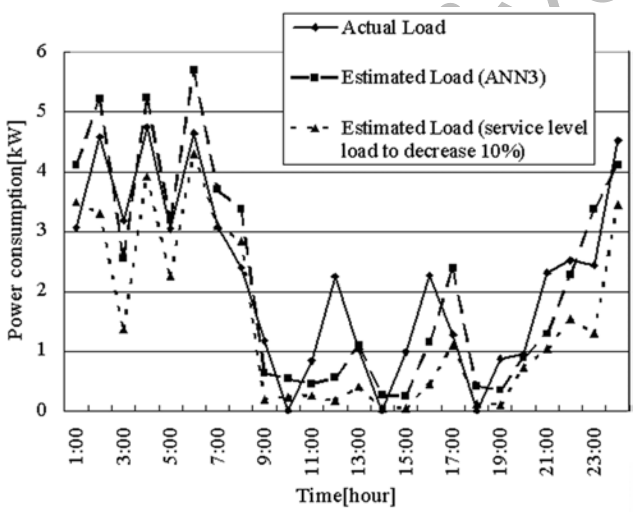


Fig. 14. Comparison of estimation of a Dehumidifier (January 30) done by reference [7] and our proposed multi-agent system, MAS.

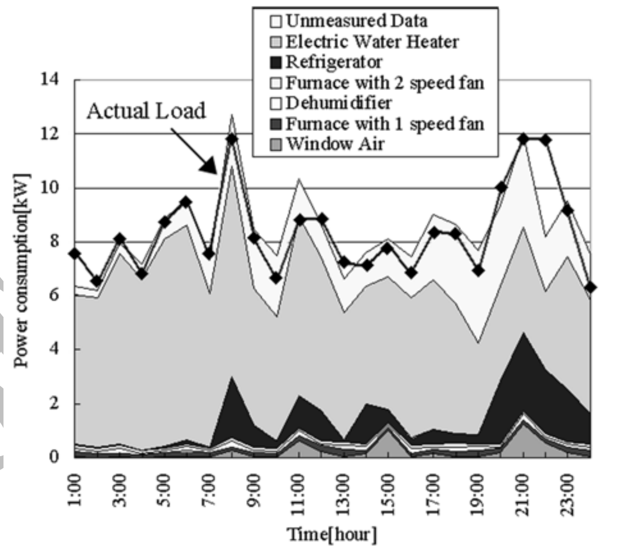


(a)

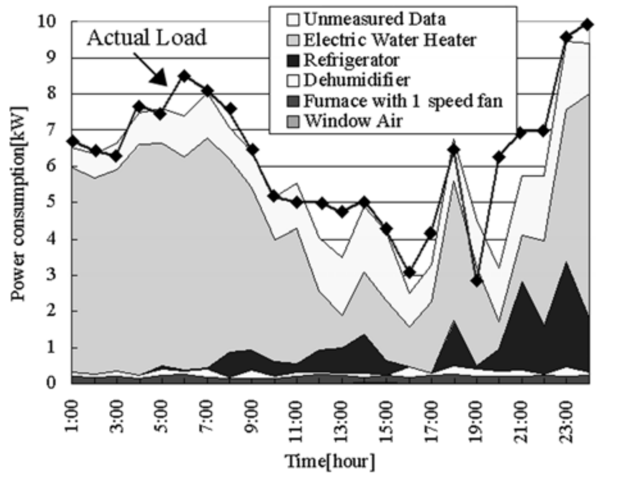


(b)

Fig. 15. Comparison of estimation of an Electric water heater (March 31) done by ANN3 and service level load: (a) with 10% increase, (b) with 10% decrease.



(a)



(b)

Fig. 16. Decomposition of load profiles of: (a) 6 appliances from the hourly service level load (Microwave load is removed from the example sets), (b) 5 appliances from the hourly service level load (Microwave and Furnace with 2 speed fan loads are removed from the example sets).

Expected benefits of this study can be summarized as follows.

1) Decomposition of service level loads into end-use load profiles gives useful information to the power utilities and helps them to avoid a large capital investment for more metering equipment. This will significantly enhance the utility planning process.

2) Increasing the sample size of end-use data would increase the power utility's confidence in the estimation of load profiles. This data is critical to future rate planning, market planning and load forecasting activities.

3) Regarding the application of multi-agent system, we understood that the scalability of the multi-agent systems is very beneficial. Since they are inherently modular, we can easily add new agents to a multi-agent. In other words, we can add new capabilities to the system.
4) Application of ANN for learning the outside environment and related inputs of this research was successful. In our opinion, ANN has many useful characteristics including learning and generalization and therefore can be designed and applied to agents to expand the information on end-use load profiles without incurring the expense of purchasing additional end-use monitoring equipment.

As for future study, there are still some rooms for further investigation. For instance, in order to generate more accurate results, more relevant data such as humidity, wind speed, type of household, location of household, structure of household and so forth should be taken into account.

REFERENCES

[1] R. Gallant, *Statistical Nonlinear Models*, New York, John Wiley & Sons, 1991, Chapter 5-7.

[2] D. Srinivasau, A. C. Liew, and C. S. Chang, "Forecasting daily curves using a hybrid fuzzy-neural approach," in *Proc. the 1994 IEE Generation-Transmission-Distribution*, vol. 141, no. 6, pp.561-567, Jun. 1994.

[3] A. H. Noureddine, A. T. Alovani, and A. Chandrasekaran, "On the maximum likehood duty cycle of an appliance and its validation," *IEEE Trans. on Power Systems*, vol. 7, no. 1, pp. 228-235, Feb. 1992.

[4] F. Sultanem, "Using appliance signatures for monitoring residential loads at meter panel level," *IEEE Trans. on Power Delivery*, vol. 6, no. 4, pp. 1380-1385, Oct. 1991.

[5] B. Kermanshahi, R. Yokoyama, and K. Takahashi, "Practical implementation of neural nets for weather dependent load forecasting and reforecasting at a power utility," in *Proc. 1996 the 12th PSCC*, pp.217-223, 1996.

[6] L. Wu and M. Niranjan, "Building energy data analysis and prediction with recurrent neural network," in *Proc. 1993 ASHRAE Annual Meeting on Building energy Predictor Shootout*, no. TR. 124.

[7] B. Kermanshahi, Y. Amano, A. Halim, and K. Takahashi, "Decomposition of end-use profiles from sites with hourly service level metering using neural nets," in *Proc. 1999 ICEE*, vol. 1, pp. 467-470, 1999.

[8] V. Lesser (eds.), *Proceedings of the1995 First International Conference on Multi-agent Systems*, AAAI Press/The MIT Press.

[9] J. Bates, "The role of emotion in believable agents," *Communications of the ACM*, vol. 37, no. 7, pp. 122-125, Jul. 1994.

[10] J. L. Deneubourg, S. Goss, N. Franks, A. Sendova-Franks, and L. C. Chretien, "The dynamics of collective sorting robot-like ants and ant-like robots," in J. Meyer and S. Wilson (eds.), *Proc. of the First Int. Conf. on Simulation of Adaptive Behavior: From Animals to Animates*, pp. 356-262, 1991, The MIT Press/Elsevier.

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