

# Non-Intrusive Appliances Load Monitoring System Using Neural Networks

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## ABSTRACT

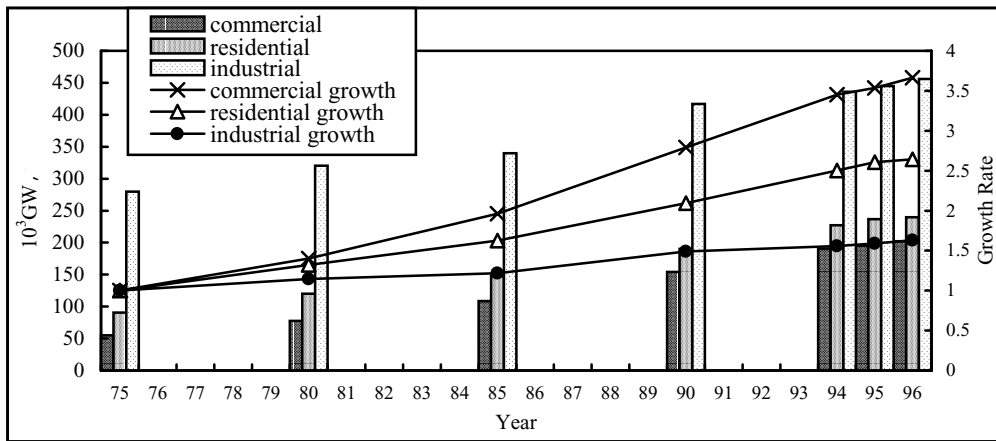
A non-intrusive appliances load monitoring system has been developed to ascertain the behavior of each electrical appliance in a household by disaggregating the total household load demand. This system does not need to intrude into a house when metering power consumption of each appliance. Therefore, the system has significant cost advantages and is less troublesome to the customers. This paper describes a non-intrusive monitoring system which is especially useful for inverter-driven appliances that frequently change their operational state. Conventional non-intrusive load monitoring systems cannot treat these inverter-driven appliances easily because of their complicated operation. In the developed system, the load consumption of household appliances is identified by the pattern recognition ability of a Neural Network (NN), which perceives the pattern of harmonics flowing out of the house. The patterns of current and phase at each harmonic order depend on what kind of appliances are in on or off. An air conditioner, a refrigerator, an incandescent lamp, a fluorescent lamp and a television set were used as household appliances to obtain training data for NN's learning. The inference ability of the NN from unknown data was simulated. From the simulation result, it was verified that the NN could identify the operating status and load consumption of an inverter-driven air conditioner from the pattern of harmonics of the total household load. For this reason, the non-intrusive appliances load monitoring system for inverter-driven appliances such as air conditioners is viewed as reliable.

## Introduction

For efficient management of electrical power companies, the prediction of peak load is one of the important factors. Precise prediction requires ascertainment of what and how household electric appliances are used, especially in the residential sector that has not yet been well investigated. In Japan, power companies monitor the usage of appliances in most case studies; however, such monitoring is not conducted very broadly. The reason is that the number of residential customers is enormous and the monitoring tools are less cost-effective. Therefore, a simple and convenient monitoring system is required for this purpose. Information gathered by the system can be used not only for efficient management but also for general promotion of energy conservation and energy efficiency.

Figure 1 shows the trend of electricity consumption in Japan ([MITI] 1998). Because the industrial sector has made extraordinary efforts in energy-saving since the oil crises, their electricity consumption growth has been slower. Meanwhile, the residential and commercial sectors both show rapid growth. Accordingly, energy conservation measures in residential and commercial sectors are marked nowadays. If a simple and convenient monitoring system becomes available, energy efficiency in these sectors can be promoted.

This paper proposes a new Non-Intrusive Appliances Load Monitoring System (NIALMS) using a Neural Network (NN) (Bishop 1995) for residential customers. The system disaggregates the total electric load to individual loads of each appliance by perceiving the pattern of harmonics flowing out of a house. It is especially useful for inverter-driven appliances that frequently change their operation modes. Pattern recognition capabilities of NN have been used to identify the operating state of the appliances. Such a system can lighten the burdens and the costs concerned with metering.



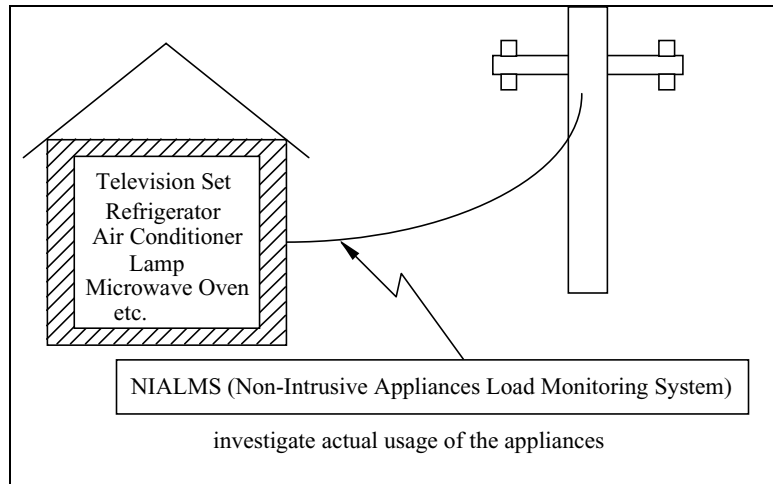
**Figure 1. Annual Electricity Consumption in Japan**

## The New NIALMS

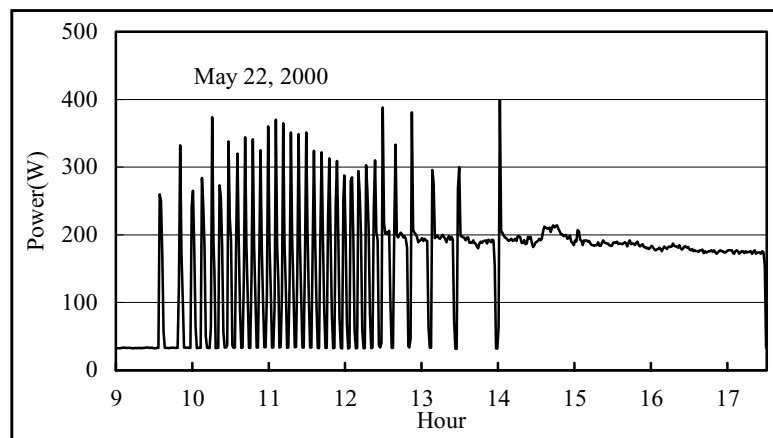
There are two general types of monitoring systems: intrusive and non-intrusive. The former is a common metering system that measures consumption load by connecting power meters to each appliance or feeder line inside a house. Since it is necessary to enter the house, this system is called “intrusive”. It can yield very accurate data but imposes costs and the burden of setting up sensors and data storage units on the households concerned. Therefore, there is an advantage to monitoring appliances from outside the home. This type of monitoring is called “non-intrusive” because there is no need to enter the house. This type infers the load of appliances using only information gathered at a revenue meter.

Figure 2 shows an outline of the NIALMS. A conventional NIALMS (Hart 1992; Norford and Leeb 1996) infers individual loads of ON/OFF appliances by checking “signatures” that provide information on their activities. A signature is described as signature space, which consists of real and reactive power found from the difference between ON and OFF activity. In other words, if a step change is detected in total load, it means that an appliance has changed its activity and can be identified by checking the signature space.

However, the conventional NIALMS encounters identification difficulty when there are inverter-driven appliances in a house. Inverter-driven appliances are difficult to discern as to their ON/OFF activity because their loads involve many usage conditions and can change smoothly and frequently, not just ON/OFF. Therefore, it is difficult to detect step changes and to check the signature space. Figure 3 shows a daily load changing of an inverter-driven air conditioner. Here, an inverter-driven appliance is one in which power is supplied through inverter circuits to make it easy and controllable.



**Figure 2. Outline of the NIALMS**



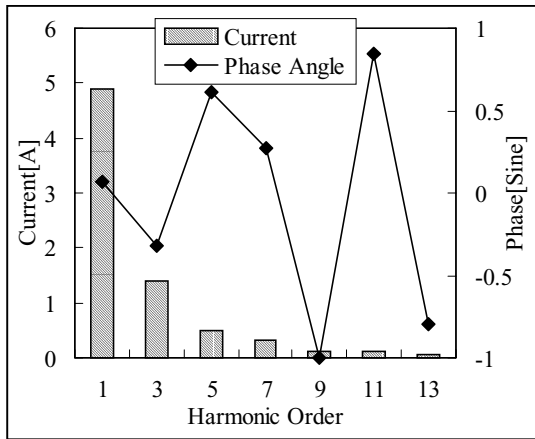
**Figure 3. Daily Load Changing of an Inverter-Driven Air Conditioner**

The new NIALMS described in this paper identifies the individual loads of electrical appliances, including inverter-driven appliances, by recognizing the patterns of each order of harmonic current and phase angle, which depend on the amount of load and which appliances are ON or OFF. The method does not require the detection of the step change. The basic idea to estimate ON/OFF states of appliances including inverter-driven appliances has already been proposed (Yoshimoto and Nakano 1998). This paper describes a further study on estimating the load consumption of each appliance.

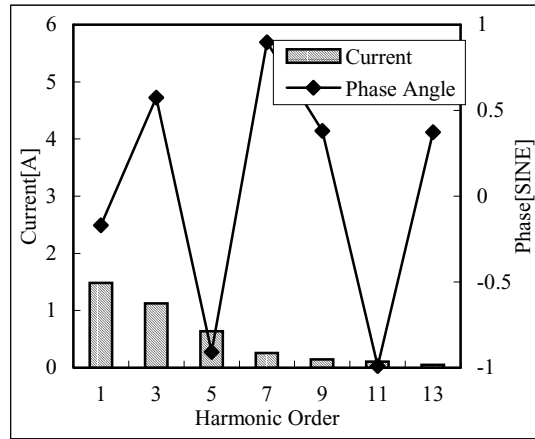
### **Relation among Operation and Harmonic Patterns**

Figures 4 through 8 show each harmonic order current and phase angle from fundamental component voltage of appliances, respectively; an air conditioner, a refrigerator, incandescent lamps, fluorescent lamps and a television set. Figures 9 through 12 show current and phase angles from fundamental component voltage of each harmonic order, in the cases that a few appliances are in operation. The load of each appliance is given in Tables 1 through 4, respectively. Each harmonic pattern shows different aspects and is found to

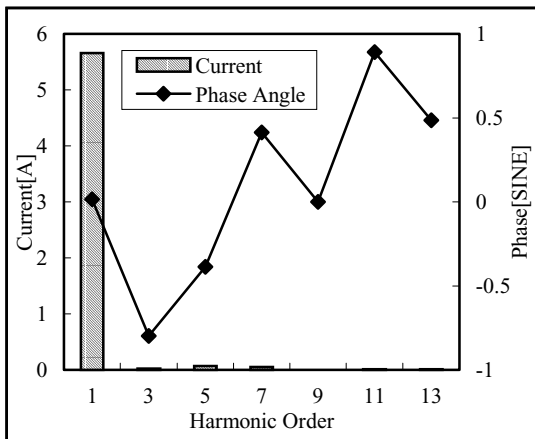
depend on how much load and which appliances are ON or OFF. The new NIALMS has noticed the patterns and inferred what is harmonic source.



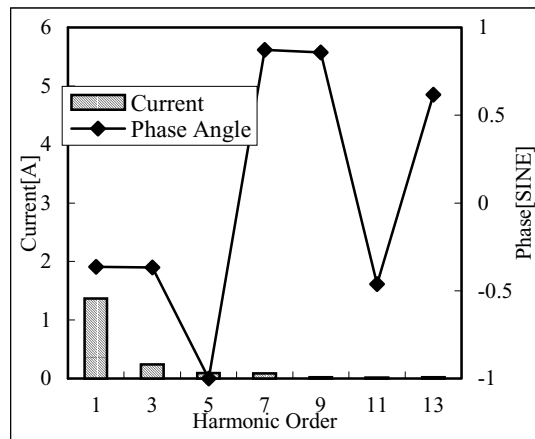
**Figure 4. Harmonic Pattern of an Air Conditioner**



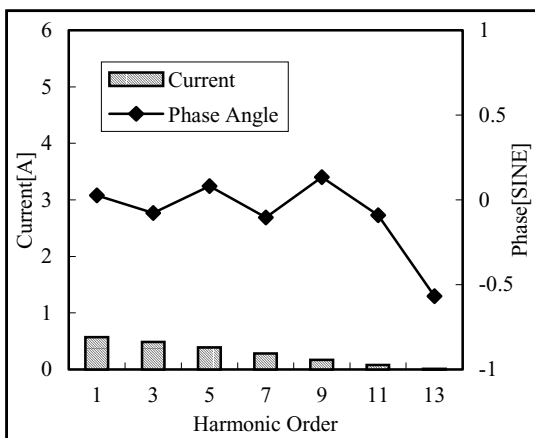
**Figure 5. Harmonic Pattern of a Refrigerator**



**Figure 6. Harmonic Pattern of Incandescent Lamps**



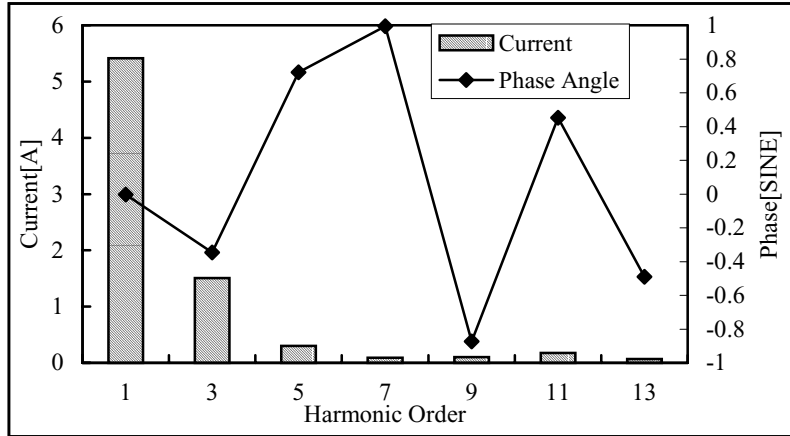
**Figure 7. Harmonic Pattern of Fluorescent Lamps**



**Figure 8. Harmonic Pattern of a Television Set**

**Table 1. Composition of Appliances (Case 1)**

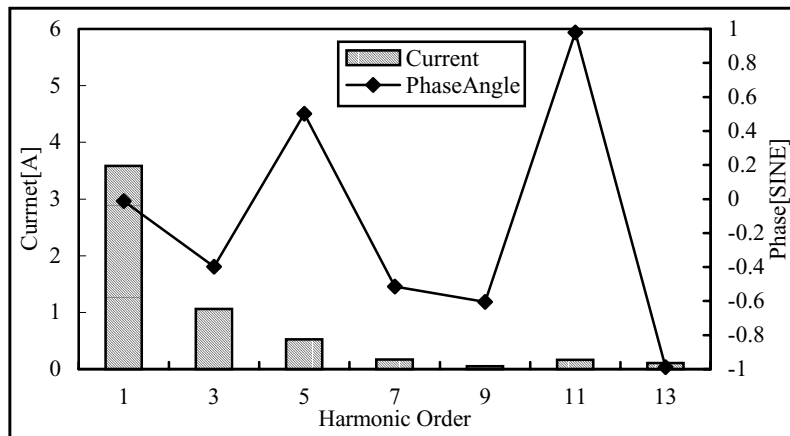
	Air Conditioner	Refrigerator	Incandescent Lamp	Fluorescent Lamp	Television Set
Power Load [W]	373	0	0	126	59



**Figure 9. Harmonic Pattern of Case 1**

**Table 2. Composition of Appliances (Case 2)**

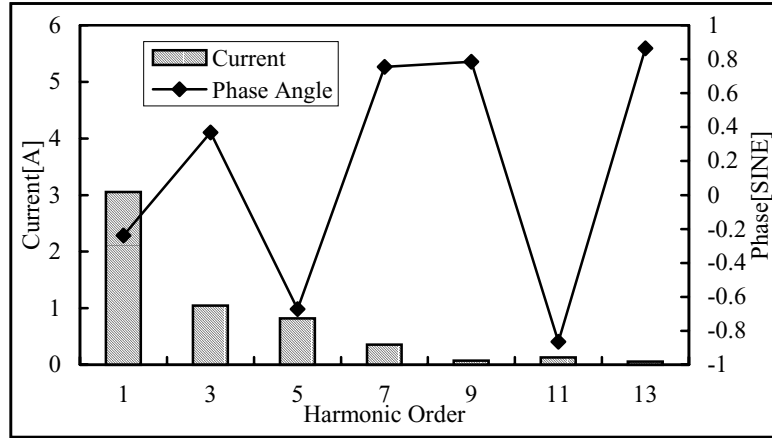
	Air Conditioner	Refrigerator	Incandescent Lamp	Fluorescent Lamp	Television Set
Power Load [W]	189	0	0	127	58



**Figure 10. Harmonic Pattern of Case 2**

**Table 3. Composition of Appliances (Case 3)**

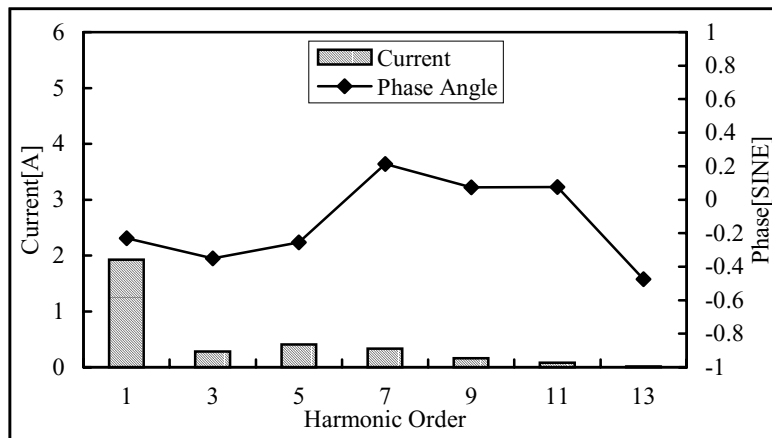
	Air Conditioner	Refrigerator	Incandescent Lamp	Fluorescent Lamp	Television Set
Power Load [W]	0	117	0	135	57



**Figure 11. Harmonic Pattern of Case 3**

**Table 4. Composition of Appliances (Case 4)**

	Air Conditioner	Refrigerator	Incandescent lamp	Fluorescent lamp	Television Set
Active Power [W]	0	6	0	132	57



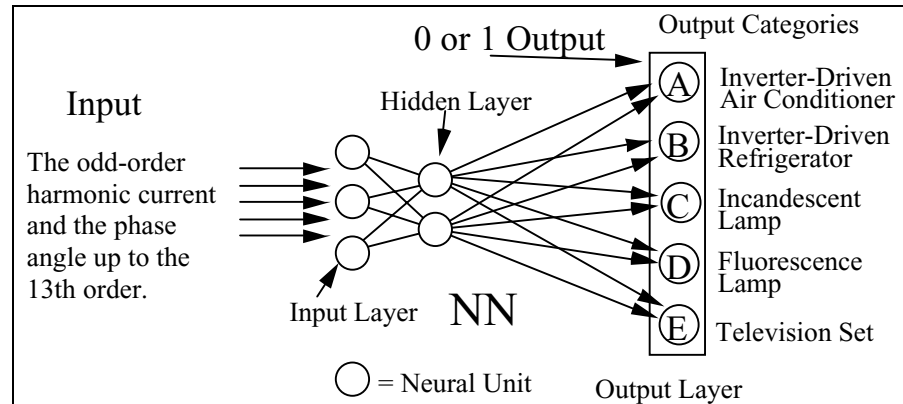
**Figure 12. Harmonic Pattern of Case 4**

A neural network for harmonic source monitoring is applied to a power system in past studies. The approach described in Hartana and Richards (1990) and Mori and Suga (1991) estimated the magnitude of harmonics using a neural network. The NN proposed in this paper is the first time in which a NN has been applied to estimate the behavior of electrical appliances for load monitoring in buildings.

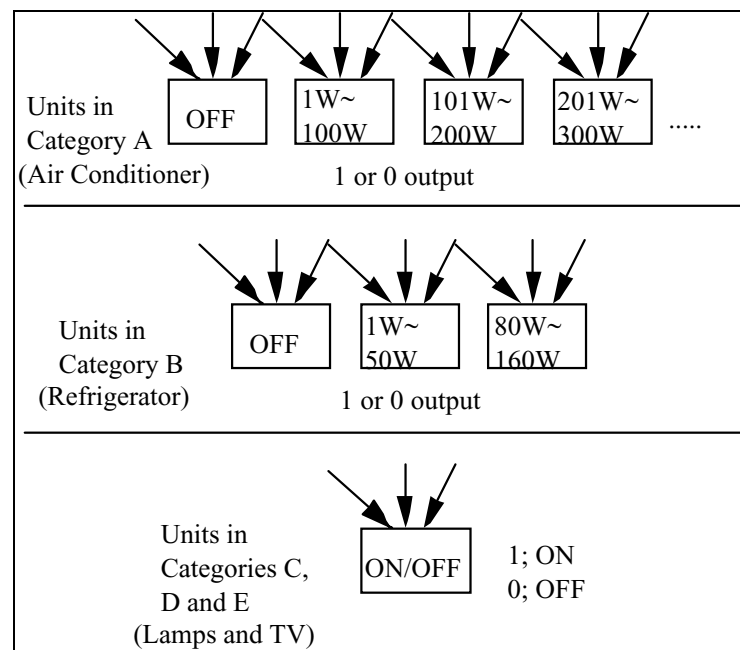
## NN for NIALMS

### Outline of the NN

Figure 13 shows an outline of the NN used for NIALMS. The odd orders of the 1st-13th harmonic current and phase angles (transferred by sine function) were input to neural units belong to an input layer on the left-hand side. The corresponding outputs, which represent the operating states (ON/OFF or load consumption) of the appliances, are output from units belonging to an output layer on the right-hand side.



**Figure 13. NN Designed for NIALMS**



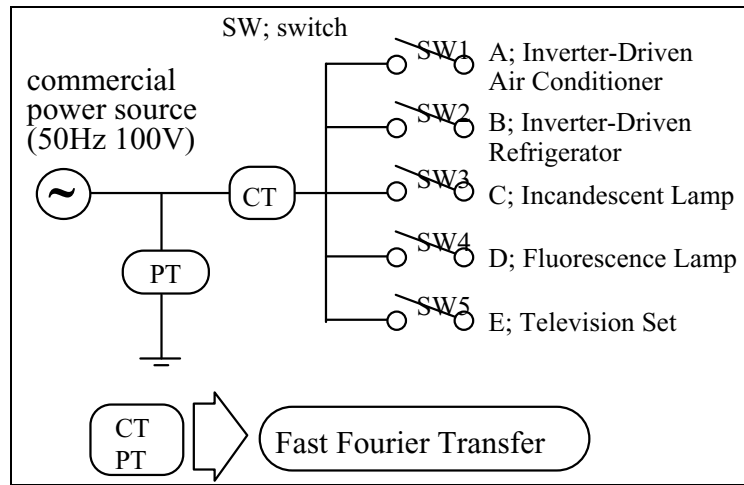
**Figure 14. Output Units Categories**

Here, the neural units in the output layer are classified into one of appliance category: A, B, C, D and E shown in Figure 13. The outputs were treated as shown in Figure 14. Category of A (an air conditioner) has several output units according to the rated power consumption, and each indicates air conditioner's load as follows. If a unit (shown as a box)

in this category has an output of 1, the air conditioner is operated in the corresponding watt range (shown in the box), if 0, it is not operated at that watt range. If the output of the OFF state unit (shown as OFF box in Figure 13) is 1, it means the air conditioner is OFF. The neural units corresponding to B (a refrigerator category) are similar to those in the air conditioner category, except for the number of output units. The refrigerator has 3 operating states; OFF, stand by (compressor OFF) and compressor ON. Therefore, the number of boxes is three and the load consumption of the refrigerator is classified in the three ranges shown in Figure 13. The number of neural units corresponding to ON/OFF appliance category such as lamps or TV (C, D and E categories) is one, and their outputs indicate ON/OFF states (shown as ON/OFF box). If an output in this category is 1, the corresponding appliance is ON, if 0, the appliance is OFF.

### Data Collection for Neural Training

Using equipment with the circuit configuration as shown in Figure 15 and a harmonic wave analyzer, harmonics for NN training are collected. The CT (Current Transducer) and the PT (Potential Transformer) in the Figure are metering-point of a sensor for the harmonics and corresponding to the entrance of the electricity feeder line or revenue meter of the house. It is possible to change the composition of target appliances by controlling switches expressed by SW.



**Figure 15. Outline of the Equipment Used for Measuring Harmonic for NN Training**

### Training the NN

Target appliances for monitoring are listed in Table 5. The number of output units is twelve: air conditioner OFF, 1-100W, 101-200W, 201-300W, 301-400W, 401-500W; refrigerator OFF, 1-50W, 80-160W; incandescent lamp ON/OFF; fluorescent lamp ON/OFF; television set ON/OFF. The number of training data for the NN is 327, collected in the way described above. The number of each training data in watt range is listed in Table 6. Switching the number of target appliances from 2 to 5 (= 26 sets) and their composition, harmonics were measured every 10 seconds for 900 seconds. That is, 90 data sets were



measured for each composition,  $90 \times 26 = 2340$  data sets. Harmonic patterns were different in every set, even with the same components, because the air conditioner and refrigerator shifted their operating mode and the harmonics of the commercial power source influenced the patterns.

The NN was trained using the popular back propagation algorithm. Ten initial states of neural connection weight were prepared through experiments, and were randomly generated (between -1 and 1), because the back propagation algorithm starts with initial connection weights and neural weights diverge dependent on initial weights.

**Table 5. Electric Appliances List**

Category	Appliance
A	Inverter-driven air conditioner (MAX.500W)
B	Inverter-driven refrigerator (MAX.160W)
C	Incandescent lamp (100Wx6)
D	Fluorescent lamp (20Wx6)
E	Television (standard 80W)

**Table 6. Number of Training Data in Each Watt Range**

	OFF	1-100W	101-200W	201-300W	301-400W	401-500W
Air conditioner	104	61	2	3	87	70
Refrigerator	OFF	1-50W	90-160W			
	143	86	98			
Incandescent lamp	OFF	ON				
	135	192				
Fluorescent lamp	OFF	ON				
	143	184				
Television set	OFF	ON				
	140	187				

**Table 7. Parameter Set for NN Training**

Number of training data	327
Number of units in a hidden layer	15
Learning rate	0.1
Sigmoid function gain	0.3
Momentum factor	0.5

The training parameters are listed in Table 7. When the absolute value difference between teacher signals and outputs of the NN was less than 0.3, or when the number of training cycles was more than 200000, training stopped. One cycle was when the NN was given a set of training data.

From numerical computation experiments, the training was on the whole successful. But each NN could not learn only one set of training data except for a NN (this NN terminated training in less than 30000 cycles), where the absolute error of the training data that was not learned was more than 0.5. Data patterns that could not be discerned were

different in each NN. Excluding these patterns, the absolute error between teacher signals and outputs was less than 0.3.

## Generalization Performance

To confirm the inference ability of the NN for unknown data (not used in training), 1500 patterns of harmonics were prepared separately and input to the 10 trained NNs. Such an inference ability of the NN is called generalization performance.

Table 8 shows the composition of unknown data. In the experiments, when an output of the NN was greater than 0.5, it was considered as 1, when lower, it was considered as 0. The NN used a sigmoid function and output 0-1 values.

The results of the generalization performance experiment are shown in Table 9. The values in Table are the number of correct answer that the NNs gave out of 1500 sets of unknown data. Here, a column "EX. NO.", which stands for Example Number, is the trained NNs number because 10 NNs were trained. In addition, the values in the "ALL" column mean the number of correct answers subjected to all appliances. The number of average correct answers for each appliance was more than 1464.6 (97.6% on average). This result implies that the harmonic pattern recognition using a NN was effective in the prototype NIALMS.

**Table 8. The Number of Unknown Data in Watt Range**

Air conditioner	OFF	1-100W	101-200W	201-300W	301-400W	401-500W
	540	260	14	14	378	294
Refrigerator	OFF	1-50W	90-160W			
	649	390	461			
Incandescent lamp	OFF	ON				
	613	887				
Fluorescent lamp	OFF	ON				
	652	848				
Television set	OFF	ON				
	630	870				

**Table 9. The Number of Correct Answer for Unknown Data (total 1500)**

EX. NO.	Air Conditioner	Refrigerator	Incandescent	Fluorescent	TV	ALL
1	1464	1486	1493	1491	1491	1460
2	1464	1481	1493	1489	1487	1450
3	1468	1474	1497	1488	1485	1451
4	1464	1485	1497	1490	1489	1458
5	1465	1479	1494	1491	1490	1454
6	1467	1486	1495	1491	1488	1460
7	1467	1472	1499	1491	1491	1448
8	1464	1488	1498	1489	1491	1456
9	1462	1475	1497	1492	1493	1448
10	1461	1475	1496	1492	1490	1444
Average	1464.6	1480.1	1495.9	1490.4	1489.5	1452.9

**Table 10. Correct Answer Rate for Unknown Data in Each Watt Range for Air Conditioner and Refrigerator**

	EX. NO.	1	2	3	4	5	6	7	8	9	10
Air Conditioner	OFF	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	not OFF	99.6	99.3	99.5	99.6	99.6	99.6	99.6	99.7	99.6	99.7
	1-100W	98.5	100.0	98.8	100.0	99.2	98.8	98.5	99.6	99.2	98.8
	not 1-100W	99.8	99.8	99.8	100.0	99.8	99.8	99.8	99.7	99.8	100.0
	1-200W	28.6	21.4	21.4	21.4	14.3	21.4	7.1	28.6	35.7	21.4
	not 101-200W	99.8	99.9	99.8	99.9	99.8	99.8	99.9	99.9	99.9	99.8
	201-300W	78.6	64.3	78.6	71.4	71.4	71.4	71.4	71.4	71.4	71.4
	not 201-300W	99.5	99.9	99.1	99.4	99.9	99.9	99.0	99.3	99.3	99.3
	301-400W	98.4	98.7	98.4	98.7	98.4	98.4	99.5	98.7	98.7	98.7
	not 301-400W	99.1	99.1	99.3	99.2	99.4	99.6	99.0	99.3	99.4	98.7
	401-500W	99.0	98.6	99.7	97.6	98.6	98.6	99.3	98.3	99.0	98.3
not 401-500W	99.3	98.8	99.3	98.7	99.3	98.8	99.4	98.8	99.3	98.8	
Refrigerator	OFF	99.2	99.1	98.9	98.9	99.1	99.1	98.0	99.2	98.2	98.5
	not OFF	99.2	98.5	99.3	99.2	99.1	99.2	98.8	99.3	98.9	98.8
	1-50W	97.9	97.4	96.7	98.2	98.2	98.5	99.0	98.7	98.5	96.9
	not 1-40W	99.5	99.5	99.1	99.3	99.2	99.5	98.5	99.5	98.8	99.2
	90-160W	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	not 90-160W	99.9	100.0	99.8	100.0	99.8	100.0	100.0	100.0	100.0	100.0

## Conclusions

In order to create a simple and convenient monitoring system, this paper proposed a new NIALMS based on NNs for household appliances. Based on training and unknown data experiments, it was verified that the NN approach can properly infer operating state of each appliance and disaggregate the total household load to the consumption load of individual appliances. This approach can be especially useful when inverter-driven appliances such as air conditioners are part of the household appliances. Incorporating NN in NIALMS makes it possible to ascertain how and what household electric appliances are used in residential sector.

In future studies, we plan to produce a portable NIALMS incorporating a NN chip and to start field tests. We also plan to apply a recurrent NN so that NIALMS can process time series data.

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