PREDICTION OF ROOM TEMPERATURE SIDE-EFFECT DUE TOFAST DEMAND RESPONSEFOR BUILDING AIR-CONDITIONING FACILITIES

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ABSTRACT

In order to evaluate side-effect of power limitation due to the Fast Automated Demand Response (FastADR) for building air-conditioning facilities, a prediction model on short time change of average room temperature has been developed. A room temperature indexis defined as a weighted average of the entire building for room temperature deviations from the setpoints. The index is assumed to be used to divide total FastADRrequest to distribute power limitation commands to each building.In order to predict five-minute-change of the index, our combined mathematical model of an auto regression (AR) and a neural network (NN) is proposed.In the experimental results, the combined model showedthe root mean square error (RMSE) of 0.23 degrees, in comparison with 0.37 and 0.26 for conventional single NN and AR models, respectively. This result is satisfactory prediction for required comfort of approximately 1 degree Celsius allowance.

KEYWORDS

neural network, auto regression, smart grid, demand response, air conditioning

1. INTRODUCTION

The future smart grid will include a large amount of renewable energy sources (RESs) such as photovoltaic systems. These RESs are notorious for output power fluctuation depending on instantaneous weather variations. As one of mitigation methods, a new technology of fast and large aggregation of power demand controls is emerging [1]. It is called smart grid demand response for ancillary services or Fast Automated Demand Response (FastADR).

A large number of office buildings' air-conditioning is one of the principal targets for the FastADR because of large volume and flexible controllability [2][3]. In order to manage the FastADR of them, however, it is necessary to predict possible amount of power curtailment before activating the FastADR. Many statistical prediction models on power consumption of air-conditioning facility have been studied using such as AutoRegression (AR) or Neural Network (NN) methods[4]-[9]. Some recent studies began to deal with fine-time-granularity power response to the FastADR of office buildings' air-conditioningfacilities [10][11]. However, regarding side-effect of the FastADR, i.e., adverse effect on comfort due to power limitation, the prediction of change in room temperature has been scarcely investigated so far.

In Japan and many other countries, Variable Refrigerant Flow (VRF) type air-conditioning facilities [12][13] are popular for small or medium size office buildings. Since a VRF facility is equipped with its embedded refrigerant control system, the instantaneous power consumption looks spontaneous from the FastADR controller's point of view. Constructing a prediction modelon the dynamic response of power consumption and resulting temperature change of the VRF air-conditioning facility is a challenging task.

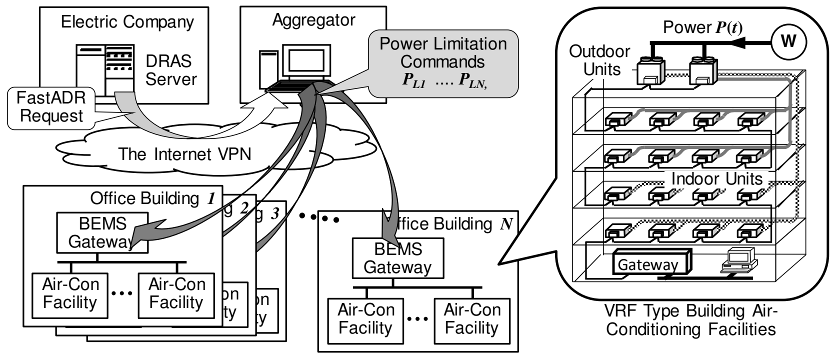

Figure 1. The conceptual diagram of the Fast Automated Demand Response Aggregation System for a widely-distributed buildings' facility loads.

Because the FastADR causes abrupt changes of power limitation, the responses of instantaneous power and room temperature show significantly non-linear and stochastic characteristics. Since NN models are known as relatively robust to the non-linearity, prediction of instantaneous power seems to be suitable with the NN modelling. On the other hand, statistical but gradual progressive changes in room temperature seem to suite well with the AR model. There are some research studies on combination of different prediction models [14]-[18]. We have applied the combination approach to obtain the cross-effect model between both the power and temperature as well as our previously proposed AR-NN combined modelling method [19].

In this paper, we propose a "room temperature index" that evaluates the FastADR's side-effect on degradation of comfort regarding room temperature. Our AR-NN Combined model for prediction of the room temperature index of 5 minutes after the FastADR activation was developed using time series data of an actual office building. In the experimental results, the Combined model showed the root mean square error (RMSE) of 0.23 degrees, in comparison with 0.37 and 0.26 for conventional single NN and AR models, respectively.

2. FastADR Power Limitation and Its Side-effect

2.1. Power Limitation Distribution for FastADR Aggregation

Figure 1 shows a concept diagram of the smart grid FastADR of a cluster of widely distributed VRF air-conditioning facilities of office buildings. Although there is only one Aggregator in the figure because of the figure space, three will be many Aggregators each of that manages its own a large number of buildings. Each Aggregator receives the FastADR request from the Demand Response Automation Server (DRAS) [20][21]in the electric company in order to compensate to the variation of RESs instantaneous power fluctuation.

Our motivation is to construct prediction model on change in the average room temperature of the building, that is to evaluate the side-effect of the FastADR of building air-conditioning facilities. The room temperature index will be used for the Aggregator todivide the DRAS's FastADR requestamount into a number of power limitation commands for each building.An example algorithm will be as follows. Firstly, the Aggregator temporally divides the DRAS's FastADR request amount into each power limitation commands in proportional to each building's current power consumption value. Then, by using the prediction model, the Aggregator evaluates the five-minute-change of room temperature index for each building. If any changes of the indexes

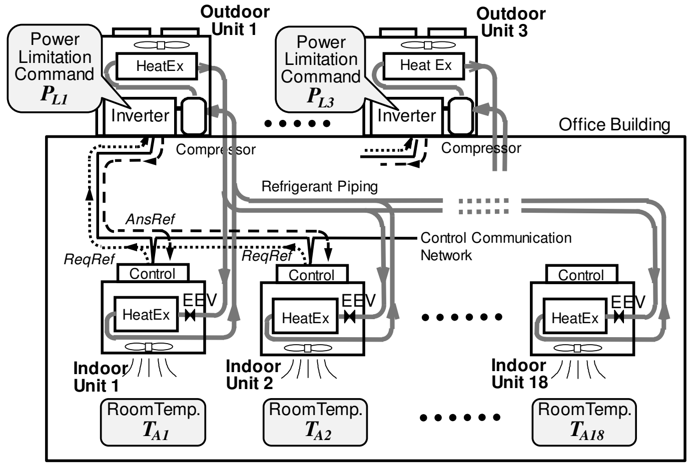

Figure 2. The refrigeration circuit of VRF type air-conditioning facilities.

are not acceptable, the Aggregator reduces the power lamination command value for the problem buildings and again distributes the revised commands to all the buildings. Such a way, the Aggregator will be able to distribute reasonably-divided power limitation commands.

2.2. VRF Type Building Air-Conditioning Facilities

Figure2 shows a refrigerant circuit of VRF air-conditioning system. An outdoor unit contains a heat exchanger, a blower fan, a refrigerant gas compressor, and its inverter. Each outdoor is connected to a number of indoor units with refrigerant gas/liquid circuit piping. Each indoor unit contains a heat exchanger, a blower fan, an electronic expansion valve (EEV), and a controller. The indoor unit controller modulates its EEV to regulate the refrigerant flow into its own heat exchanger according to heat load of the indoor unit.

Each indoor unit periodically sends a requesting refrigerant flow, *ReqRef* message to the outdoor unit. The outdoor unit periodically sums up these requests and modulates its total output flow by varying speed of the compressor. The outdoor unit then distributes to each indoor unit an answering refrigerant flow,*AnsRef* message. Each indoor unit regulates the opening of its EEV according to the value of each *AnsRef* message.

The power consumption is determined by both the power limitation command from the Aggregator and the above-mentioned *ReqRef-AnsRef*refrigeration circuit control. Using this control each room temperature is controlled to each setpoint by adjusting the inverter power continuously. In addition, state-of-the-art refrigeration controlssuch asoil-return exceptionoperations or refrigerant pressure adjustment controls and so on are superimposed time to time.. The total air-conditioning facilities of the entire building is far more complicated than residential air-conditioners. Therefore, short time prediction onthe response of room temperature change due to the power limitation to the inverter-driven compressors is a challenging task.

In case of steady states, air-conditioning heat balancing can be calculated by traditionalmethod. However, it is difficult to construct a dynamic response mathematical model for room temperature response due to step change of power limitation. For the total building, there may be more than 100 room temperature points. It is almost impossible to make a response prediction model from physical differential equations for each building' structure and facilities' construction.

We decided to construct a statistical prediction model from time-series data of air-conditioner's operations.

2.2. Room Temperature Index

An index in some form is needed to evaluate occupants' comfort degradation as the side effect due to the FastADR power limitation. We focus on the deviation of room temperatures from corresponding setpoint temperatures. Since a FastADR Aggregator service provider has to take care of many buildings, the number of pairs of room temperatures and setpoints will be hundreds or thousands.

As mentioned above, the motivation of introducing the room temperature index is to obtain a reference for division of the total FastADR request amount into each Power Lamination Command for each building according to each building's air-conditioning situation. Only relative index between buildings is enough instead of each room temperature. Therefore, we take the average of each deviation of room temperature from the corresponding setpoint for the total building. As each indoor unit capacity and room space area varies significantly, the rated air-conditioning capacity of the indoor unit is used as the weight averaging to take each room's size effect into account.

We define theroom temperature index of a building as the weighted averageroom temperature deviation $T_{SA}(t)$ at the discrete time t as

$$T_{SA}(t) = \{\sum_{m=1}^{M}\big(T_{Am}(t) - T_{Sm}(t)\big)C_m\}/\sum_{m=1}^{M} C_m \qquad (1)$$

where m(= 1, 2, ...) is the number of indoor unit,M is total number of indoor units in the building, C_m is each indoor unit's rated cooling capacity, $T_{Am}(t)$ is measured room temperature, $T_{Sm}(t)$ is setpoint temperature, of the mth indoor unit at one-minute discrete time t.

Since the room temperature index$T_{SA}(t)$ is the weighted average of deviations of room temperature from the setpoint, we assumed $T_{SA}(t)$ represents general index of buildings residents' comfortableness by its smallness. In general, the absolute value of $T_{SA}(t)$ in sufficiently comfortable room is said to be less than approximately 1.0 degreeCelsius.

3.AR-NN Combined Model

3.1. Prediction Model for Room Temperature Index

Our AR-NN combined model was proposed for modelling the above-mentioned room temperature index change by the FastADR power limitation. In the Combined model, the inputs are time series data of $P(t)$s and $T_{SA}(t)$s, and the output is $T_{SA}(t+t_F)$ of a few minutes later $t_F$from the time t when the power limitation$P_L(t)$was changed.

Our Combined modelcontains individual two models, an NN model and an AR model, as shown in Figure 3. In Figure 3, t is discrete time of 1 minute unit, $P_L(t)$ is the power limit, $P(t)$ is the power consumption at t, $T_{SA}(t)$ is the room temperature index at t, $T_O(t)$ is outdoor temperature of the building, and $T_{SA}(t+1)$ is 1 minute future value.

The Combined model collects and complements input data to vectors of time series data in pre-processing. First, all of input data up to the present are collected in the pre-processing. Second, missing data in collected input data are complemented with liner interpolation using existing data of before/after missing. Finally, the pre-processing passes necessary data from its collected data

Table 1. Outline of a sample office Building

Item	Specification
Type of building	General purpose office
Dimension	2 story, area app. 3000 m^2
Structure of building	Steel frame concrete building
No. of outdoor units	3 outdoor units
No. of indoor units	18 indoor units

Figure 3. The structure diagram of the AR-NN Combined model on the room temperature index for the FastADR Aggregation side-effect prediction.

to the NN and AR models. The submitted data sets are a part of whole data sets, which are selected for training the models.

The NN and AR models predict the room temperature index individually, and $T_{SA}(t+t_F)$ is given by the following combining equation with predicted value notation * as $T^*_{SA}(t+t_F)$

$$T^*_{SA}(t+t_F) = \alpha f^{NN}(\boldsymbol{x}(t)) + (1-\alpha) f^{AR}((\boldsymbol{x}'(t)) \quad (2)$$

In equation (2), a set of inputtime-series data is pre-processed to make input vectors of $\boldsymbol{x}(t)$ and $\boldsymbol{x}'(t)$ to the NN and AR model, respectively.The outputs $y^{NN}(\boldsymbol{x}(t))$ and $\boldsymbol{y}^{AR}(t+1)$ from the NN and AR model are combined with coefficients $\alpha$and 1- α. The coefficientα is ranged between [0, 1]. In order to $f^{NN}(\boldsymbol{x})$ is an output function of NN model by input $\boldsymbol{x}$, and$f^{AR}(\boldsymbol{x})$ is an output function of the AR model by input $\boldsymbol{x}$.

$$\boldsymbol{x}(t) = [T_{SA}(t), T_{SA}(t-1), T_{SA}(t-2), P(t), P(t-1), P(t-2), P_L(t+1), P_L(t), T_O(t), T_O(t-1), T_O(t-2)]^T \quad (3)$$

$$y^{NN}(\boldsymbol{x}(t)) = Sigmoid\left(\sum_{j=1}^{J} w_j \times Sigmoid\left(\sum_{i=1}^{I} u_{ij} \times \boldsymbol{x}_i(t)\right)\right) \quad (4)$$

$$Sigmoid(z) = 1/(1+e^{-az}) \quad (5)$$

$$T^{NN}_{SA}(t+t_F) = y^{NN}(\boldsymbol{x}(t)) = f^{NN}(\boldsymbol{x}(t)) \quad (6)$$

where $y^{NN}(\boldsymbol{x}(t))$ is the output of the NN for predicted value at 5 minutesafter from the time t, i(= 1, 2, ...) is the node number in the input layer, I(= 11) is the total number of input layer's nodes, j(= 1, 2, ...) is the node number in the hidden layer,J(= 15) is the total number of hidden layer nodes. The model parameteru_{ij} is the weight of connection to the hidden layer nodes from the input layer nodes, w_j is the weight of connection to the output layer node from the hidden layer nodes. The vector$\boldsymbol{x}_i(t)$ is the input from the pre-processing, specifically, the power limit from $P_L(t)$ to $P_L(t+1)$, the power consumption from $P(t-2)$, $P(t-1)$ to $P(t)$, the room temperature index from $T_{SA}(t-2)$, $T_{SA}(t-1)$ to $T_{SA}(t)$, and outside temperature from $T_O(t-2)$, $T_O(t-1)$to $T_O(t)$. The function$Sigmoid(z)$ was used as the activation function for any real number variable z.

3.2. Auto Regressive Model

In our previous research work [19], we proposed the AR-NN Combined model for the above-mentioned room temperature index change by the FastADR power limitation. In the Combined model, the inputs are time series data of $P(t)$,$T_{SA}(t)$, and the output is $T_{SA}(t+1)$ at one minute after from the power limitation.

The AR model predicts the room temperature index $T_{SA}(t+1)$ at 1 minute after the current time t using preceding input data received from pre-processing. Its prediction after 5 minutes $T_{SA}(t+5)$ is obtained by repeating the 1 minute prediction five times using the pervious AR predictions.

Our AR model equations are

$$\boldsymbol{x}'(t) = [T_{SA}(t), P(t), P_L(t)]^{\mathrm{T}} \tag{7}$$

$$\boldsymbol{y}^{AR}(t+1) = \sum_{l=0}^{L-1} \begin{bmatrix} A_{11}^{(l)} & A_{12}^{(l)} & A_{13}^{(l)} \\ A_{21}^{(l)} & A_{22}^{(l)} & A_{23}^{(l)} \end{bmatrix} \boldsymbol{x}'(t-l) \tag{8}$$

$$\boldsymbol{y}^{AR}(t+1) = [T_{SA}(t+1),\ P(t+1)]^{\mathrm{T}} = [y_1^{AR}(t+1),\ y_2^{AR}(t+1)]^{\mathrm{T}} \tag{9}$$

$$T_{SA}^{AR}(t+t_F) = y_1^{AR}(t+t_F) = f^{AR}(\boldsymbol{x}'(t)) \tag{10}$$

where $\boldsymbol{y}^{\mathrm{AR}}(t+1)$ is predicted state vector after 1 minute from the current time t, $\boldsymbol{x}(t-l)$ is input state vector at $t-l$, and $\boldsymbol{A}$ is an AR coefficient matrix. The elements of input/output state vectors consist of power limit $P_L(t)$, actual power consumption $P(t)$, room temperature index$T_{SA}(t)$. The AR model's order L was decided as $L = 7$ using the AIC (Akaike Information Criterion) method [22]. Each element of the AR coefficient matrix $\boldsymbol{A}$ was decided by the least mean square method using the same training data as the NN case.

4. Experiments on Prediction

4.1. Time Series Data from an Office Building

Table 1 shows overview of the sample building air-conditioning facilities. The time series data of the power consumption $P(t)$, room temperature index $T_{SA}(t)$, and power limit $P_L(t)$were acquired from an actualoffice building of two stories which contained eighteen indoor units and three outdoor units of air conditioning systems. The interval of the time series data was one minute. The building's power consumption was controlled by changing the power limitation$P_L(t)$ every ten minutes.

The number of measured time series data sets was 8640 including 864power limitationcommand step changes, and the number of usable data sets was3400 including 340 limitation changes. These measured time-series data were divided into three groups, namely, the training, optimization, and test data sets of166, 78, and 96, respectively.

4.2. Model Construction and Experiment Results

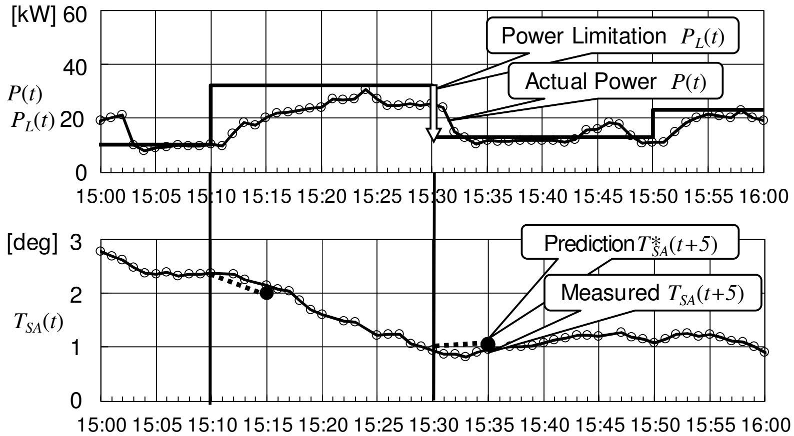

Figure 4. An example of comparison between model prediction and actual measurement of the room temperature index $T_{SA}(t+5)$.

The model parameters of the single NN and AR models weredetermined using the above-mentioned training time-series data sets in advance of the model prediction tests. The combination coefficient α of the Combined model was decided as an optimized value by a statistical measure, root mean square error (*RMSE*) to the optimization data sets of 78 which are not used in the model training and tests.

To construct the Combined model for predicting the room temperature index $T_{SA}(t+5)$, the NN and AR models learned using training data for construction the Combined model. The each variable of state vector of NN was normalized in ranged of [0.0, 1.0] and learned using 100,000 times of each training data sets. In addition, final NN were experimentally chosen by results of this training process trial. The AR was learned by least-squares method using the same training data sets.

Figure 4 shows an example of prediction test. After the power limitation $P_L(t)$ is activated as shown by the arrow at 15:30, the room temperature index $T_{SA}(t)$ changed its trend from decreasing to level. The difference between predicted$T^*_{SA}(t+5)$ and actual$T_{SA}(t+5)$ was measured many times. We evaluated the performance of the prediction model using the root mean square error (*RSME*)was use as a statistical measure.

$$RMSE = \sqrt{\frac{1}{D}\sum_{d=1}^{D}\left(T_{SA}^{*(d)}(t+5) - T_{SA}^{(d)}(t+5)\right)^2} \tag{11}$$

where D is the total number of test data sets, d(= 1, 2, ...) is thenumber of each power limitationstep response data set.

The best combined model for the optimization data was obtained when α = 0.53. The *RSME* of the best combined model was compared with those of the NN and the AR models in Figure5. The *RMSEs* for the NN, AR, Combined models were 0.37, 0.26, and 0.23, respectively. It means 38 % and 12 % relative improvements of *RMSE* were achieved.

5. DISCUSSION

The reason why the improvement of *RMSE* from the NN model to the Combined model was more effective than that from the AR model seems to be that the target time-series data characteristics

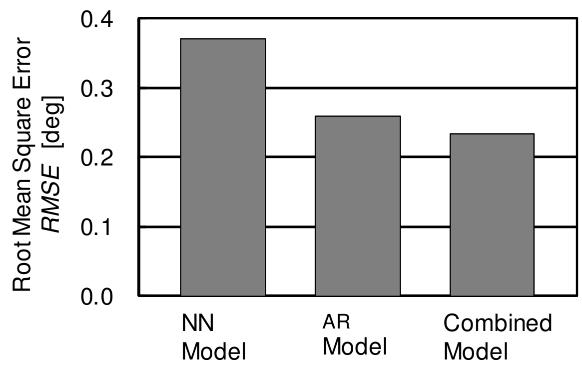

Figure 5. Comparison of the root mean square error among the NN, AR, and Combined models for the room temperature side-effect prediction.

of the weighted average of room temperature deviation from the setpoint are governed by linear data generation source. From a physical point of view, the dynamic behavior of the room temperature is a linear heat transfer process. This physical understanding agrees our result that the *RSME* of the linear AR model is more similar that that of the non-linear NN model.

So far, in research studies on the FastADR using air-conditioning facilities, side-effect on the room temperature, i.e., residents' comfort caused by power limitation has not been dealt quantitatively [2][3][10]. This research has shown a possibility that the FastADR power limitation commands to air-conditioning facilities can be divided and distributed maintainingeach building's comfort level kept within the pre-determined range.

Our room temperature index represents the total average of the entire building for power limitation command division and distribution to each building. Of course, each room might have different allowance for the room temperature change, priority allocation to each indoor unit can be adjusted by the local controller in each building as long as the total average room temperature change is kept within a criterion. Our prediction model for the room temperature index will provide an effective management method on this issue.

6. CONCLUSIONS

In this research work, a prediction model on short time change of average room temperature has been developed. A room temperature index is defined as a weighted average of the entire building for room temperature deviations from the setpoints. In order to predict five-minute-change of the index, our combined mathematical model of an auto regression and a neural network is proposed.

In the experimental results, the Combined model showed the root mean square error (*RMSE*) of 0.23 degrees, in comparison with 0.37 and 0.26 for conventional single NN and AR models, respectively. This result is satisfactory prediction for required comfort of approximately 1 degree Celsius allowance.

REFERENCES

[1] O. Ma, N. Alkadi, P. Cappers, P. Denholm, J. Dudley, S. Goli, M. Hummon, S. Kilcote, J. MacDonald, N. Matson, D. Olsen, C. Rose, M. Sohn, M. Starke, B. Kirby, & M .O'malley, "Demand Response for Ancillary Services", IEEE Trans. on Smart Grid, Vol. 4, No. 4, pp1988-1995, 2013.

[2] H. Hao, Y. Lin, A. S. Kowli, P. Barooah, and S. Meyn, "Ancillary Service to the Grid Through Control of Fans in Commercial Building HVAC Systems," IEEE Trans. Smart Grid, vol. 5, no. 4, pp. 2066–2074, 2014.

[3] Y. Lin, P. Barroah, S. Meyen, and T. Middlekoop, "Experimental Evaluation of Frequency Regulation From Commercial Building HVAC Systems", IEEE Trans. on Smart Grid, Vol. 6, No. 2, pp.776-783, 2015.

[4] T. Nohara and C. Ninagawa, "Study on dynamic characteristics simulation of air conditioners", Trans. JSME C, Vol.53, No.494, pp.2115-2120, 1987. (in Japanese)

[5] M. Kasahara, T. Matsuba, U. Hashimoto, A. Kimbara, K. Kamimura, and S. Kurosu, "Optimum preview control for HVAC system", ASHRAE Trans., Vol.104, Part1, pp.502-513, 1998.

[6] J. White and H. Reichmuth, "Simplified method for predicting building energy consumption using average monthly temperature", IECEC96, Vol.3, pp.1834-1839, 11-16 Aug. 1996.

[7] T. Nohara and C. Ninagawa, "Study on dynamic characteristics simulation of air conditioners", Trans. JSME C, Vol.53, No.494, pp.2115-2120, 1987. (in Japanese)

[8] M. Kasahara, T. Matsuba, U. Hashimoto, A. Kimbara, K. Kamimura, and S. Kurosu, "Optimum preview control for HVAC system", ASHRAE Trans., Vol.104, Part1, pp.502-513, 1998.

[9] J. White and H. Reichmuth, "Simplified method for predicting building energy consumption using average monthly temperature", IECEC96, Vol.3, pp.1834-1839, 11-16 Aug. 1996.

[10] C. Ninagawa, S. Kondo, S. Isozumi, and H. Yoshida : "Fine-time-granularity fast demand control of building HVAC facilities for future smart grid," in Proc. IEEE Int. Conf. on Innovative Smart Grid Technologies, ISG T Europe 2012, pp. 1-6 , 2012.

[11] K. Suzuki, C. Ninagawa, H. Yoshida, S. Kondo, J. Morikawa, T. Kanbe and Takao Aoki : "Smart Grid ADR Aggregation Delay Model on Large-Scale Distributed Building HVAC Facilities", in Proc. IEEE Innovative Smart Grid Technologies, ISGT Europe 2013 , 2013.

[12] W. Goetzler, "Variable refrigerant flow systems", ASHRAE Journal, Vol. 49, No. 4, pp. 24-31, 2007.

[13] C. Ninagawa, T. Sato, Y. Kawakita, and N. Matsumura, " Virtual Wattmeter Power Consumption Billing Division for Building Air-Conditioners Supporting User's Energy Saving Intention", The Institute of Electrical Engineers of Japan, IEEJ Trans. on Electrical and Electronic Engineering, Vol. 5, pp. 695-700, 2010.

[14] G. Zhang, "Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model", Neurocomputing, Vol. 50, pp.159-175, 2003.

[15] L. Xuemei, D. Lixing, S. Ming, X. Gang, and L. Jibin, "A novel air-conditioning load prediction based on ARIMA and BPNN model", APCIP2009, Vol.1, pp.51-54, 18-19 July, 2009.

[16] F. Pan, M. Xia, and E. Bai, "A New Hybrid Model for Time-series Prediction", 8th IEEE Int. Conf. on Cognitive Informatics, ICCI'09, pp.281-286, 2009.

[17] E. Mangalova and E. Agfonov, "Time Series Forecasting using Ensamble of AR models with Time-varying Sttucture", IEEE Conf. on Evolving and Adaptive Intelligent Systems EAIS2012, pp.198-203, 2012.

[18] K. Bakhshayesh and M. Ghofrani, "Development of a Robust Identifier for NPPs Transients Combining ARIMA Model an EBP Algrorithm", IEEE Trans. on Nuclear Science, Vol. 61, No.4, pp.2383- 2391, 2014

[19] T. Fukazawa, Y. Iwata, J. Morikawa, and C. Ninagawa, "Stabilization of Neural Network by Combination with AR Model in FastADR Control of Building Air-conditioner Facilities", IEEJ Trans. on Electrical and Electronic Engineering, Vol. 11, No. 1, 2016, (in press).

[20] C. Ninagawa, T. Iwahara, and K. Suzuki, "Enhancement of OpenADR Communication for Flexible Fast ADR Aggregation Using TRAP Mechanism of IEEE1888 Protocol", in Proc. IEEE Int. Conf. on Industrial Technologies, ICIT2015, Seville, Spain, 2015.

[21] OpenADR Allience, "OpenADR 2.0 Profile Specification B Profile", Document No. 20120912-1, p14, 2013

[22] P. Brockell and R. Davis, "Introduction to Time Series and Forecasting, 2nd Edition", Springer, 2002.