New Service Design Based on Power Demand Forecasting Methods Using Real Customer Data

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Abstract. This paper proposes a new service called Demand Fix. Demand Fix is a service that determines a daily power demand of the next day using power demand forecasting methods. The errors between actual values and predictive values are absorbed by introducing a storage battery. In previous works, in order to forecast the power demand, Auto Regressive Integrated Moving Average (ARIMA) forecasting model and multiple regression analysis and so on were introduced. However, they don't forecast the step-by-step power demand. Also, a practical service using the power demand forecasting is not mentioned.In this paper, a new power demand forecasting method, 48step method, is proposed. The accuracy is compared with the previous methods using step-by-step power demand data, and 48step method has a highest accuracy. Moreover, Demand Fix is simulated with 48step method and the practicability is shown. A required capacity of a storage battery is indicated.

Keywords: demand forecasting, power demand, simulation, service, multiple regression analysis

1. INTRODUCTION

Stabilizing power supply in a power system is necessary for any industries and leads lower electric power charges for users. To stabilize power supply, electric power demand forecasts play an essential role, as they provide the basis for making decisions in power system planning and operation. A great variety of mathematical methods have been used for demand forecasting.

In previous works, in order to forecast the power demand, Autoregressive Integrated Moving Average (ARIMA) forecasting model and multiple regression analysis and so on were introduced. However, they don't forecast the step-by-step power demand. Also, the practical service using the power demand forecasting is not mentioned.

In this paper, a new electric power demand forecasting method, 48step method, is proposed. The accuracy is compared with the previous methods using step-by-step power demand data which were acquired in real houses.

Moreover, a new service called Demand Fix is proposed. Demand Fix is a service that determines a daily power demand of the next day using power demand forecasting methods. The errors between actual values and predictive values are absorbed by introducing a storage battery.

2. METHODS

In this section, three power demand forecasting methods are explained. The first two, the exponential smoothing forecasting model and Autoregressive Integrated Moving Average (ARIMA) forecasting model, are existing method. The third one is a new method, called 48step method.

2.1. Exponential smoothing forecasting model

Exponential smoothing was proposed in the late 1950s and has motivated some of the most successful forecasting methods. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older.

In this paper, the simplest of the exponentially smoothing methods naturally called “simple exponential smoothing” (SES) is compared with other methods.

SES represented by the following formula.

$$pd_i = \alpha \times d_{i-1} + (1-\alpha) \times pd_{i-1}$$
$$= pd_{i-1} + \alpha \times (d_{i-1} - pd_{i-1})$$

pd_i : Predictive value of i term
d_i : Measured value of i term
α : Smoothing constant $(0 < \alpha < 1)$

The rate at which the weights decrease is controlled by the parameter α. In this paper, α is fixed to 0.5 because this method is no more than comparison one.

2.2. Autoregressive Integrated Moving Average (ARIMA) forecasting model

ARIMA models provide another approach to time series forecasting. Exponential smoothing and ARIMA models are the two most widely-used approaches to time series forecasting, and provide complementary approaches to the problem. While exponential smoothing models were based on a description of trend and seasonality in the data, ARIMA models aim to describe the autocorrelations in the data.

In this paper, a seasonal ARIMA is applied because power demands are seasonal data. A seasonal ARIMA model is formed by including additional seasonal terms in the ARIMA models. One shorthand notation for the model is as follows.

$$ARIMA(p,d,q) \times (P,D,Q)S$$

p : Non-seasonal AR order
d : Non-seasonal differencing
q : Non-seasonal MA order
P : Seasonal AR order
D : Seasonal differencing
Q : Seasonal MA order
S : Time span of repeating seasonal pattern

2.3. 48step method

It is known that power demands and temperatures have a correlation. In previous works, the temperature is introduced as explanatory variables to forecast the power demand.

In fact, power demand is approximated by a quadratic curve as shown in Figure 1. Figure 1 shows the relationship between power demand and temperature. When the temperature is high and low, the power demand becomes great. The data were acquired in Koriyama city, Fukushima.

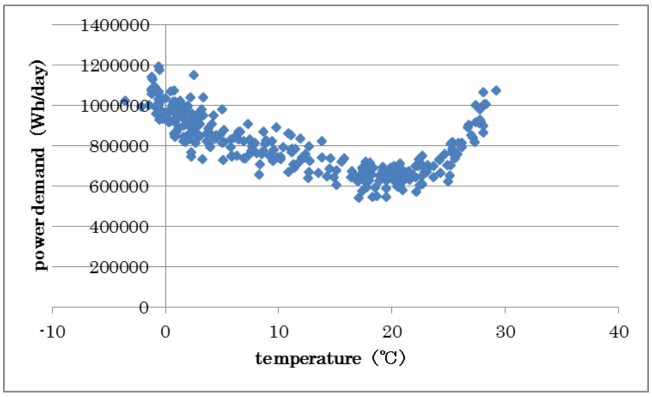

Figure 1 the relationship between power demand and temperature in Koriyama city

The new method proposed in this paper utilizes this relationship. The new method, called 48step method, divides a day into 48 steps and forecasts the power demand of each step.

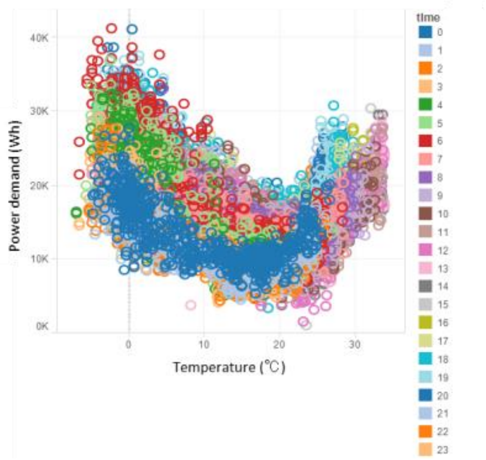

Figure 2 the relationship between power demands and temperatures every hour

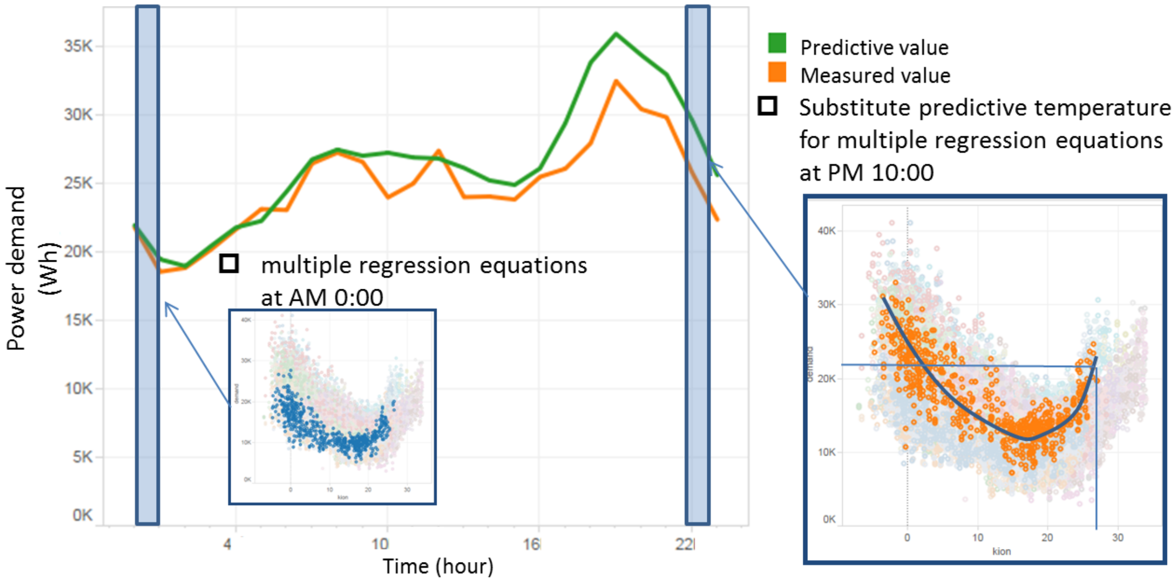

Figure 3 the schematic chart of 48step method

Figure 2 shows the relationship between power demands and temperatures every hour (to clearly display, divided into not 48 steps but 24steps). It shows the same relationship as Figure 1, so the way 48step method divides a day into 48 steps seems valid.

Figure 3 shows the schematic chart of 48step method. The procedure of 48step method is as follows:

1. The data of power demand are aggregated every 30 minutes and create 48 aggregations.
2. Calculate a multiple regression in each aggregation.
3. Substitute a predictive temperature for multiple regression equations of each aggregation.

The novelty of this method is as follows:

- Dividing a day into 48 steps makes it possible to forecast the step-by-step power demand.
- It doesn't needs high amount of calculation than methods using machine learning.
- Because of subdivision, there won't be a major deviation.

3. ERROR COLLECTING

Considering Demand Fix, the errors cumulated in a day should be reduced as much as possible. So in this paper, an error collecting is applied. The error collecting is as follows:

1. A sum of power demands in a day is forecasted.
2. Predictive values (at 30-minute intervals) are multiplied as the sum of the predictive values equals the forecasted power demand in a day.

$$P_{new}(d,s) = P(d,s) \times \frac{P_{day}(d)}{\sum_{s=1}^{48} P(d,s)}$$

$P_{new}(d,s)$: Modified value of s step of d day

$P(d,s)$: Predictive value of s step of d day

$P_{day}(d)$: Predictive value of a sum of power demand in a day

The reason why this error collecting is applied is that a power demand at one-day intervals can be forecasted more accurately than one at 30-minute intervals.

A method applied in forecasting power demands at one-day intervals is a multiple regression of temperatures.

4. CASE STUDY

Three forecasting methods and the modified values are compared in this section. The real customer data are used. Moreover, Demand Fix is simulated with the most accurate method.

4.1. Evaluation

In this paper, CRE (Cumulative Relative Error) is introduced as an evaluation value.

$$CRE = MAX\left(\frac{\left|\sum_{s=1}^{k}\{D(d,s)-P(d,s)\}\right|}{\sum_{s=1}^{48} D(d,s)}\right)\times 100$$

$D(d,s)$: Measured value of s step of d day
$P(d,s)$: Predictive value of s step of d day

The reason CRE is introduced is that considering Demand Fix, error of the day is absorbed by introducing a storage battery, and the required capacity of the storage battery should be indicated.

Also, the number of days whose CRE is more than 10% is counted. The less number is, the more effective the method is in Demand Fix.

4.2. Conditions

In this case study, three methods mentioned in section 2 are compered by real data. A full detail of the data is as follows:

- place

Koriyama city, Fukushima, Japan

- date

From Nov. 1, 2014 to Aug, 9, 2015

- The number of household

25

- Intervals

At 30-minute intervals

As shown in Figure 4, the data from Nov.1, 2014 to Jun. 30, 2015 are used for training, and from Jul.1, 2015 to Jul.21, 2015 are used for forecasting.

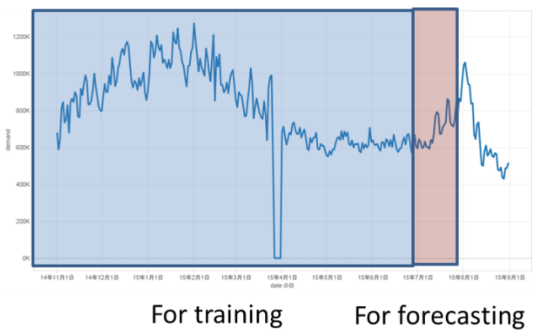

Figure 4 the data used in the case study

4.3. Result

4.3.1. Exponential smoothing forecasting model

The predictive value and the modified value are shown in Figure 5. A daily CRE is shown in Figure 6, and the summary is shown in Table 1.

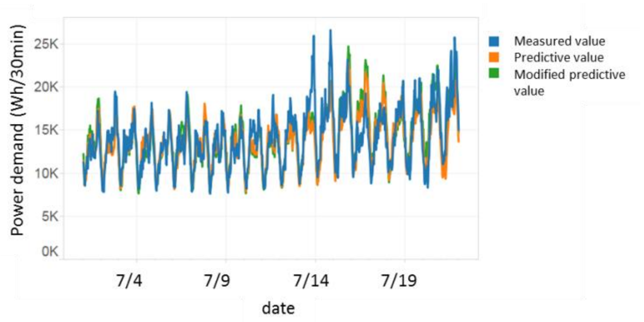

Figure 5 power demands of measured value and predictive value and modified predictive value (Exponential smoothing forecasting)

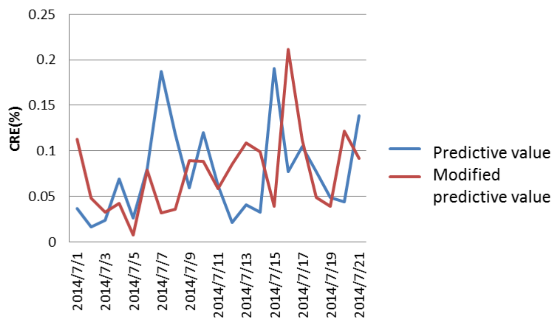

Figure 6 a transition of CRE (Exponential smoothing forecasting)

Table 1 results of Exponential smoothing forecasting method

	Exponential smoothing forecasting	Exponential smoothing forecasting(error collecting)
the number of days whose error is more than 10%	6	5
Proportion of days whose error is more than 10%	0.285714	0.238095

4.3.2. Autoregressive Integrated Moving Average (ARIMA) forecasting model

As the same way, the predictive value and the modified value are shown in Figure 7. A daily CRE is shown in Figure 8, and the summary is shown in Table 2.

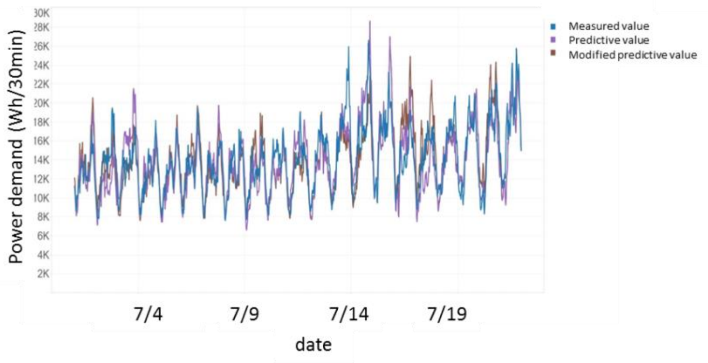

Figure 7 power demands of measured value and predictive value and modified predictive value (ARIMA forecasting method)

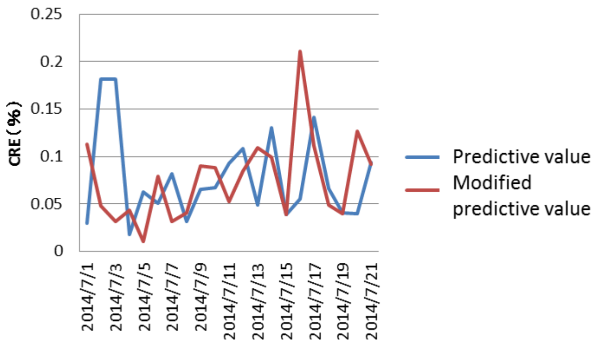

Figure 8 a transition of CRE (ARIMA forecasting method)

Table 2 results of ARIMA forecasting method

	ARIMA	ARIMA(error collecting)
the number of days whose error is more than 10%	5	5
Proportion of days whose error is more than 10%	0.238095	0.238095

4.3.3. 48step method

As to the proposed method, the predictive value and the modified value are shown in Figure 9. A daily CRE is shown in Figure 10, and the summary is shown in Table 3.

As a result, the number of days whose CRE is more than 10% is the least in step48. So the proposed method is the most accurate of three methods in this case study.

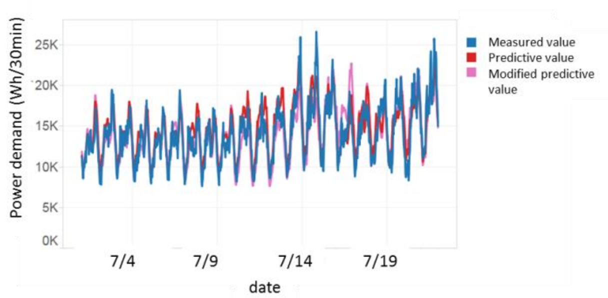

Figure 9 power demands of measured value and predictive value and modified predictive value (step48 method)

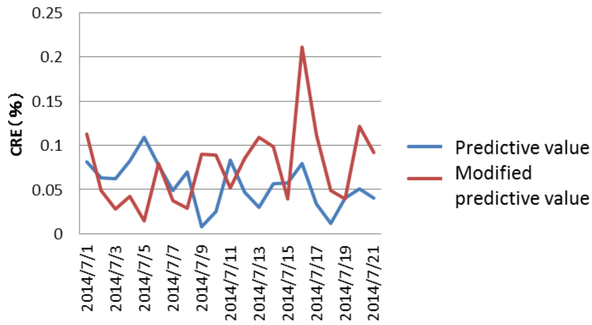

Figure 10 a transition of CRE (step48 method)

Table 3 results of step48 method

	step48	step48(error collecting)
the number of days whose error is more than 10%	1	5
Proportion of days whose error is more than 10%	0.047619	0.238095

4.4. SIMULATION

In this section, Demand Fix is simulated with the most accurate method, 48step method.

Shown in Figure 11, Demand Fix is feasible in one week introducing a storage battery of 15kWh, 6kWh per 10 households.

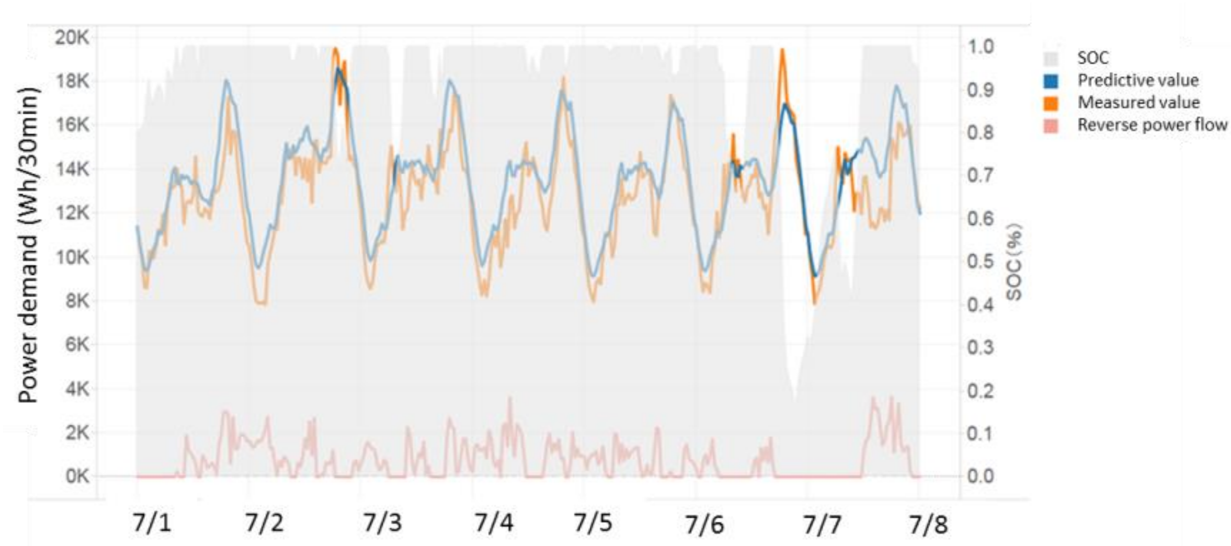

Figure 11 A simulation of Demand Fix

Also, in order to absorb errors of all days, a storage battery of 76kWh is needed in this case study as shown in Figure 12. As the same way, in order to absorb errors of 90% of days, a storage battery of 57kWh is needed.

If Demand Fix is applied to practice in this area, introducing a storage battery of 57kWh would be valid considering cost and performance.

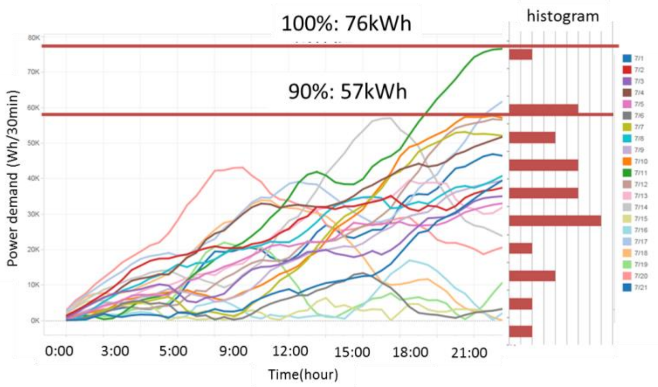

Figure 12 the change with time of daily cumulative errors and histogram of the days

Figure 13 shows CRE in a whole year including training data. The proportion of days that the errors are within 10% is 88%, so about 90% of days in a whole year is guaranteed that Demand Fix is practicable.

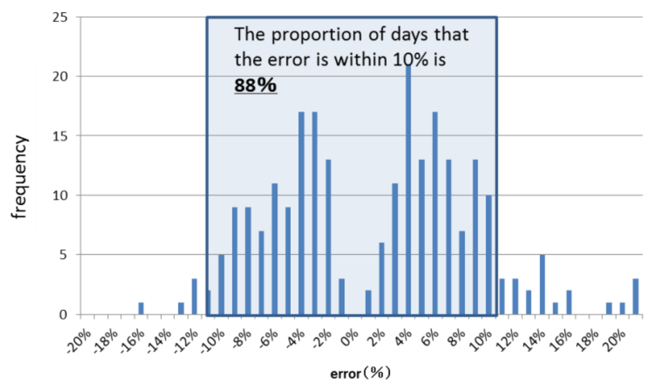

Figure 13 CRE in a whole year including training data

5. CONCLUSION

In this paper, a new power demand forecasting method (48step method) is proposed. The accuracy is compared with the previous methods using step-by-step power demand data, and 48step method has a highest accuracy. Moreover, Demand Fix is simulated with the 48step method and the practicability is shown. The required capacity of the storage battery is indicated.

However, the case study is restrictive because a forecasted period of time is only three weeks. We would like to consider another case study and evaluate 48method and simulate Demand Fix in further research.

References

Oppenheim, Alan V.; Schafer, Ronald W. (1975). Digital Signal Processing. Prentice Hall. p. 5. ISBN 0-13-214635-5.

Brown, Robert G. (1956). Exponential Smoothing for Predicting Demand. Cambridge, Massachusetts: Arthur D. Little Inc. p. 15.

Park, D. C., El-Sharkawi, M. A., Marks, R. J., Atlas, L. E., & Damborg, M. J. (1991). Electric load forecasting using an artificial neural network. Power Systems, IEEE Transactions on, 6(2), 442-449.

Chow, T. W. S., & Leung, C. T. (1996). Neural network based short-term load forecasting using weather compensation. Power Systems, IEEE Transactions on, 11(4), 1736-1742.