ISSN 1975-8359(Print) / ISSN 2287-4364(Online)
The Transactions of the Korean Institute of Electrical Engineers Vol. 66, No. 4, pp. 621~628, 2017
http://doi.org/10.5370/KIEE.2017.66.4.621

신경회로망을 이용한 마이크로그리드 단기 전력부하 예측

Short-Term Load Forecast in Microgrids using Artificial Neural Networks

정 대 원† · 양 승 학** · 유 용 민*** · 윤 근 영*
(Dae-Won Chung · Seung-Hak Yang · Yong-Min You · Keun-Young Yoon)

Abstract - This paper presents an artificial neural network (ANN) based model with a back-propagation algorithm for short-term load forecasting in microgrid power systems. Owing to the significant weather factors for such purpose, relevant input variables were selected in order to improve the forecasting accuracy. As remarked above, forecasting is more complex in a microgrid because of the increased variability of disaggregated load curves. Accurate forecasting in a microgrid will depend on the variables employed and the way they are presented to the ANN. This study also shows numerically that there is a close relationship between forecast errors and the number of training patterns used, and so it is necessary to carefully select the training data to be employed with the system. Finally, this work demonstrates that the concept of load forecasting and the ANN tools employed are also applicable to the microgrid domain with very good results, showing that small errors of Mean Absolute Percentage Error (MAPE) around 3% are achievable.

Key Words : Microgrid, Short-term load forecast, Neural networks, Back-propagation, Weather factors

1. Introduction

One of the most remarkable changes from the traditional energy production and distribution system is that most power generation is decentralized to smaller plants located near the end-use points called microgrids. A microgrid is a localized physical space consisting of distributed power generation, storage, and consumption. The need for achieving a balance between electric power generation and the demand of consumers has added to the emergence of smaller power generation and demand environments, in which adaptation of production to load can be performed much more dynamically due to their distributed smaller elements and the geographical proximity of all elements in the microgrids. In order to increase sustainability and optimize resource consumption, electric utilities are constantly trying to adjust power supply to the demand in real time. This new concept and physical distribution of microgrids will require the deployment of intelligence that controls the behavior of the different smart elements of the grid. Figure 1 shows a hypothetical microgrid including distributed generation, end-point users and storage elements. One of the most important techniques is the disaggregated load forecasting, that allows smart elements in the grid to react in advance to the demand. Microgrids that utilize modern IT and communication technologies have become a global trend. Forecasting of 1 day ahead grid load (electricity usage) is an important task to provide intelligence to the smart gird. Accurate forecasting will enable a utility provider to plan the resources and also take control actions to balance the supply and demand of electricity. Short-term load forecasting (STLF) deals with load forecasting from one hour up to one week ahead. Mid-term load forecasting is related to the time period from a few days to a few weeks, and long-term load forecasting is made for the period of one to several years. The conventional load forecasting methods of linear regression and time series have been used highlight the time role, without considering the external factor effects. In order to improve the accuracy of the forecast result, a wide variety of techniques for load forecasting has been reported in many literatures such as linear regression, exponential smoothing, ARMA models [1], and data mining models [2,3]. Data mining techniques like artificial neural networks (ANN)[2], fuzzy logic [5] and support vector machines [6] have been widely employed for load forecasting.

In this paper, we propose new ANN-based architectural model for STLF in the microgrids by applying new distributed-intelligence technologies, which are expected to be incorporated into different components of the grid. The

† Corresponding Author : Dept. of Electrical Engineering, Honam University, Korea.
E-mail: dwchung@honam.ac.kr
* Dept. of Electrical Engineering, Honam University, Korea.
Received : November 23, 2016; Accepted : February 27, 2017

back-propagation algorithm is proposed an ANN methodology in order to increase the accuracy of the forecast result in case of irregular weather conditions such as typhoons and weekends during the summer season. However, the conventional methods do not expose uniform performance for every day of the year. In particular, for anomalous weather conditions and social events, the methods have a tendency to show conspicuous accuracy deterioration. Furthermore, the tendency raises the reliability and stability problems of the conventional load forecasting methods.

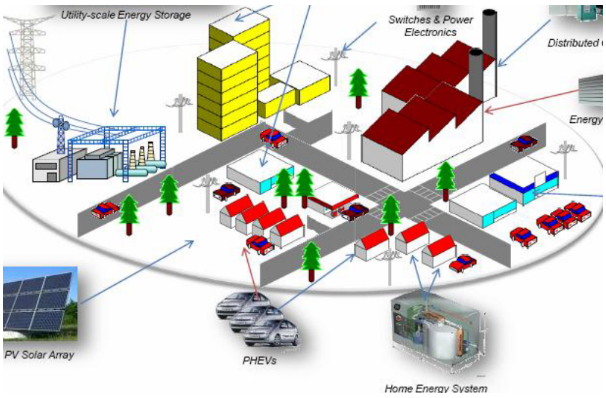


Fig. 1 Microgrid example

2. Characteristics of Electrical Loads

2.1 Load Patterns of the Microgrid System

A microgrid that supplies electric power only to small villages and islands is usually capable of controlling electric power loads that will range between thousands of kilowatts to hundreds of megawatts Fig. 2 illustrates the hourly load curves for Gosado-island in Korea in February 3, 2015. The figure shows daily and weekly load variations; the load behavior for weekdays (Tuesday through Friday) has almost the same pattern but small random variations from varying consumers' activities, weather conditions, etc. The weekday load pattern is different from the Saturday, Sunday, and Monday load patterns. Comparing weekday loads with Saturday loads, the level of Saturday loads is relatively low during the p.m. The level of Monday loads during the a.m. influenced by Sunday is very low. These phenomena equally affect Monday loads during the a.m. Therefore daily load curves are classified as weekday and weekend-day (holiday) patterns. However, the daily electric load pattern is normally related to the pattern of the previous day and other calendar data. More specifically electric consumption highly depends on the hour of the day, and the load curves of the previous day. This previous day load curve actually contains a lot of information about other conditions of the season and weather [17]. Therefore, load forecasting is performed on the basis of the previous day hourly load curves, aggregated daily load forecast, and calendar variables (day of the week, month, etc.). Electric load highly varies between workdays and weekends; electric demand on a public holiday is similar to that on Sundays.

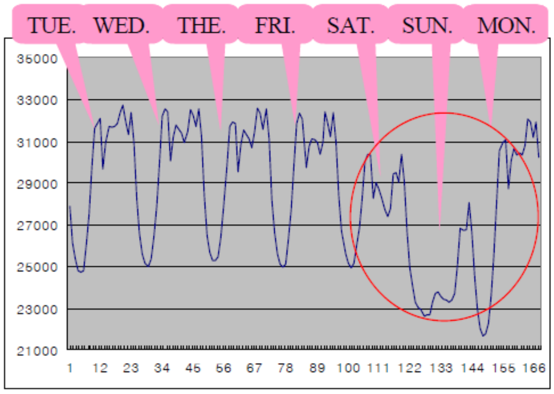


Fig. 2 Hourly load pattern over a week

2.2 Factors influencing the Load Patterns

The behavior of a microgrid system load depends on a number of factors as follows;

(1) Time and Seasonal factors: The principal of time seasonal effects, weekly daily cycle, legal and religious holidays play an important role in influencing load patterns. Seasonal effects determine utilities peaking (summer/winter) and also bring out structural modifications in electricity consumption patterns. The weekly daily cycle of the load is a consequence of the work-rest pattern of the service population. The load decreases considerably on holidays. The tendency of people to have extended weekends could also affect the loads on the days preceding and following holidays. In the summer season, the load demand strongly depends on the temperature than in the winter season. Other weather factors are negligible on the load demand because it has a meaningless correlation coefficient. The input load data consists of hourly data for three days, which are one day before, two days before, and one week before the day [17].

$$L_h = \frac{L(d-1,h) + L(d-2,h) + L(d-7,h)}{3} \tag{1}$$

where L_h is the input load variable, d is a day, and h is an hour.

(2) Weather factors: Significant changes in load patterns are due to meteorological factors as most of the utilities have large components of weather sensitive load such as room heating, air conditioning, and agricultural irrigation. The load level fluctuates with the climatic conditions and has high correlation with area temperature, rainfall, snowfall etc. Their influence on the system load varies not only between winter and summer, but also between peaks and valleys of the same day. For a system covering a vast geographical area with wide variations in climate, several weather variables in several areas may need to be considered to account for the variations in the system load.

In order to improve the accuracy of short term load forecasting, the weighting values of the temperature and dew point in every hour was proposed [16]. The weather weight (W_h) is calculated under the condition of the eq.2.

$$W_h = \mu \Delta T_d + \gamma \Delta D_d \tag{2}$$

where μ is the weighting factor of the temperature change and γ is the weighting factor of the dew point variance, which is calculated under the conditions of Table 1. ΔT, and ΔD are the variances between one day ahead forecast temperature and dew point.

Table 1 Load demand changing with temperature and dew point variation

Temperature	Increase		Decrease	
Dew Point	Increase	Decrease	Increase	Decrease
Load Demand	Sensitive Increase	Sensitive Increase	Sensitive Decrease	Sensitive Decrease

If $\Delta T_h = T_{present} - T_{before}$ is larger than 0, the temperature is increased. In this situation, the weight increase variance is adjusted by the dew point variance.

$$\Delta D_h = D_{present} - D_{before}$$

On the other hand, if ΔT_h is less than 0, the weight decrease variation is adjusted by the dew point variance, ΔD_h. Fig. 3 shows the relationship among the weather elements that are the load demand, the temperature and the dew point.

(3) Economic factors: Economic perspective such as a rate of population growth or activation of economies [12]

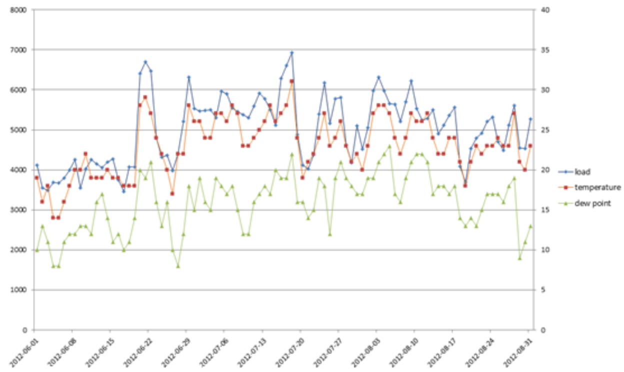


Fig. 3 relationship among the weather elements

has relevance to load demand. These include random disturbance loads such as vehicle chargers, sudden load changes. Social events, special TV programs whose effect on the load is not known a priori could cause sudden and unpredictable variations in load. Economic factors are much more difficult to apply for a short-term load forecasting model because of the complicated statistical methods that need a lot of time and efforts.

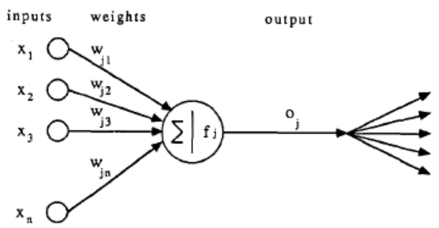
Thus the load does not satisfy the superposition principle i.e. the load is not necessarily the sum of linear independent variables, but it is rather a nonlinear system. As commonly known, nonlinear problems are often difficult to solve and much less understood than linear problems.

3. Application on Artificial Neural Networks

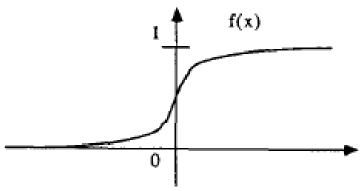
3.1 Model of Artificial Neural Networks

An artificial neural network (ANN) is defined as a highly connected ensemble of signal processing elements called neurons, which processes information by its dynamic state response to external inputs.

The ANN is very practical forecasting technology in short-term electric load forecasting fields, especially for nonlinear data. Fig. 4 shows the architecture of an ANN. It consists of an input layer, one (or more) hidden layers, and an output layer. Each layer employs several neurons and the output of each neuron is connected as input to all the neurons of the next layer multiplied by different weights. Each layer also employs a bias term that also provides an input to all the neurons of the next layer multiplied by different bias weights. Signals flow into the input layer and are propagated through the hidden layers to the output layer where the output signal is produced.



(a) Mathematical model of neuron



(b) Sigmoid function of signal transfer

Fig. 4 Architecture of ANN

3.2 Back-propagation Learning Algorithm

Back-propagation Learning (BPL) Algorithm is the most commonly used method and is a supervised learning method for time series prediction, pattern recognition as well as short term load forecasting. The BPL algorithm aims to reduce error between the calculated value and the desired output value using the gradient decent search method [4].

In the forward pass, the input data is propagated, layer by layer and all the weights are fixed. During the backward pass, all weights are adjusted to reduce the error in accordance with the error correction rule. The error signal is propagated backwards through the network against the direction of synaptic connections. Each hidden node updates the weights that were propagated back [16]. The input value is conveyed to the hidden layers using eq. (3).

$$net_{pj} = \sum_{j} \omega_{ij} O_{pi} + \theta \tag{3}$$

$$O_{pj} = f_j(net_{pj}) = \frac{1}{1+e^{-net_{pj}}} \tag{4}$$

where, i is the number of input layers and j is the number of hidden layers. ω_{ij} is the weight of the connection from unit i to unit j. θ is the bias of the hidden layer, net_{pj} is the weighted sum of the inputs. O_{pj} is the j-th component of the actual output pattern produced by the network representation with input pattern p. Next, eq. (3) transfers the result of the total weight into the next hidden layer through the sigmoid function, eq. (4). Next, we compute the weight update for the back propagation. First, the error E is calculated using eq. (5).

$$E_p = \frac{1}{2} \sum_{k} (T_{pk} - O_{pk})^2 \tag{5}$$

where k is the number of output layers and T_{pk} is the target output for the kth component of the output pattern for pattern p and O_{pk} is the kth component of the actual output pattern produced by the network representation with input pattern p. The error of neuron kth is calculated by equation (6) and each hidden layer's error is calculated by equation (7).

$$\delta_{pk} = (T_{pk} - O_{pk}) f_j^{'}(net_{pk}) \tag{6}$$

$$\delta_{pj} = O_{pj}(1 - O_{pj}) \sum_{k} \delta_{pk} \omega_{kj} \tag{7}$$

The rule of adjusting weights can be derived using eq. (8).

$$\Delta\omega_{ji}(n+1) = \eta \delta_{pj} O_{pj} + \alpha \Delta\omega_{ji}(n) \tag{8}$$

where, η is the learning rate parameter and α is the momentum constant to determine the effect of past weight changes. $\Delta\omega_{ji}$ is used to update each hidden network weight for correcting errors.

3.3 Proposed ANN Architecture

(1) Input/Output Variables Selection

Selecting Input variables is very important to apply the multilayer feed forward neural network model for forecasting the load demand [11]. There is a high correlation between load demand and three factors that are categorized as the time factors, weather factors, and economic factors as mentioned in Section 2. The three-layer architecture employed in this study is proposed as shown in Fig. 5. It has 63 input neurons, 70 hidden neurons, and 24 output neurons. Table 2 defines the input and output of the neural network. The 63 input neurons consist of the load profiles of 2 days before, weather index, seasonal index, a day of the week and a flag of holiday. The 24 output neurons are the forecasted load of 24 h of D-day.

(2) Temperature Weight Generation

In order to improve the accuracy of short term load forecasting, we use the weight value of the temperature and dew point for every hour. The weight value of the temperature is composed of two parts, which are the

Polynomial Regression curve and the variation of the weather elements data. Dew point weight value is used to adjust the bias of the weather weight that is related to the load demand and temperature. Load demand is closely related to the temperature and dew point as shown in Section 2.

(3) Data Normalization

Once the historical data is gathered, the next step in training is to normalize all the data so that each value falls within the range from -1 to +1 by dividing the values into the maximum variables value. This prevents the simulated neurons from being driven too far into saturation.

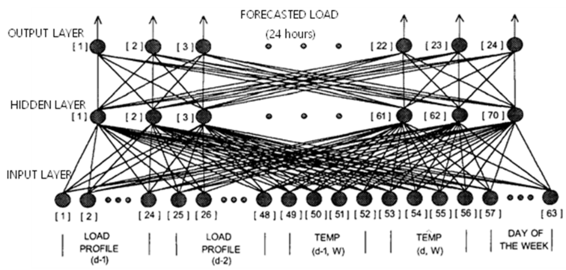


Fig. 5 Proposed ANN Architecture for short term load forecast

Table 2 ANN inputs and outputs

Inputs	Notation	Description
1~24	$L(d-1,h)$; $h=1,24$	24h Load of Previous day
25~48	$L(d-1,h)$; $h=1,24$	24h Load of 2 days before
49~52	$T(d,n)$; $n=1,4$;	4 Temperature index of D-day
53~56	$S(d,n)$; $n=1,4$	4 Season index of D-day
57~62	$W(d,n)$; $n=1,6$	Day of the week
63	$H(d,n)$; $n=1$	Holiday flag of D- day
Outputs	Notation	Description
1~24	$\hat{L}(d,h)$; $h=1,24$	24h Load Forecast of D-day

(4) Training

Prior to operation, the ANN has to be trained. During this training stage, the ANN network is confronted with a series of inputs coupled with the real expected output, that is, a set of inputs is associated to the real load curve that the system would have had to forecast. During this training, the internal weights of the ANN are adjusted to produce the appropriate outputs. Optimization of ANN - both to determine the number of neurons in the hidden layer and to establish the best training algorithm - is usually performed by a heuristic method. In our case, we decided to use an automated script where all parameters were modified (number of neurons in the hidden layer, training function, network performance function during training, etc.), calculating the estimation error for several test runs for each combination of parameter values. The best results were obtained with a total of 70 neurons in the hidden layer, the Bayesian Regulation Back-propagation training function and the Sum Squared Error network performance function. The proposed architecture is trained by using a back propagation algorithm [4,16] with Matlab SIMULINK NN Toolbox. The performance of the proposed neural network based STLF model was tested using hourly load data. Fig. 6 shows the work flow for this study. Comparison of 24 h ahead load forecasting and exact load is shown below:

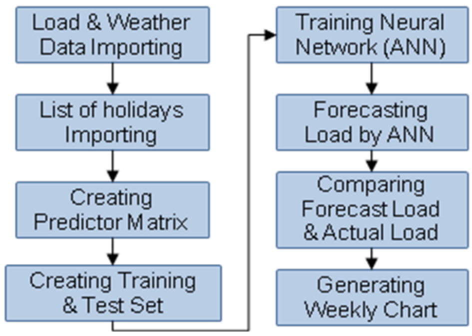


Fig. 6 Training and Simulation Work Flow

4. Case Study and Discussions

Once the network is trained, a forecast is performed for the testing set; a forecast load curve is generated for each datum and the daily average error is estimated; average errors in weekday are displayed in Figure 7 together with the mean value, $\pm 1\sigma$ and standard $\pm 2\sigma$ deviations. The mean error of the complete testing phase yielded a value of 2.4037%. Figure 8 shows one of the weekly charts and figure 9 shows one of the daily charts of comparison between actual and predicted load. As shown in Figure 8, the daily mean error is within the mean standard deviation range, which means that errors ranged between 1.45% and 3.35%, which are fairly good results. The reason why the highest mean errors occur on Fridays, Saturdays and Sundays is that the training set (load curve) is more scattered; as a result, data uncertainty is higher in weight adjustment after training, and errors increase.

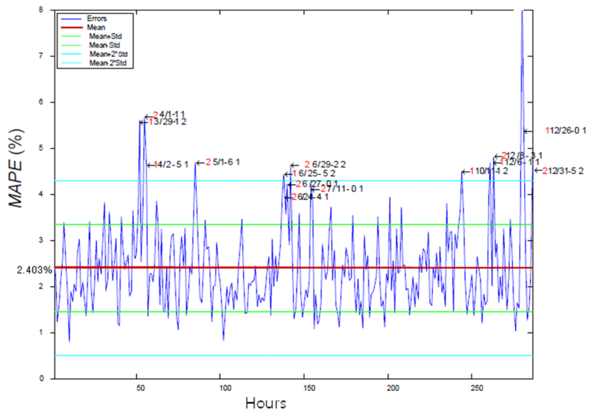


Fig. 7 MAPE measurement in weekday

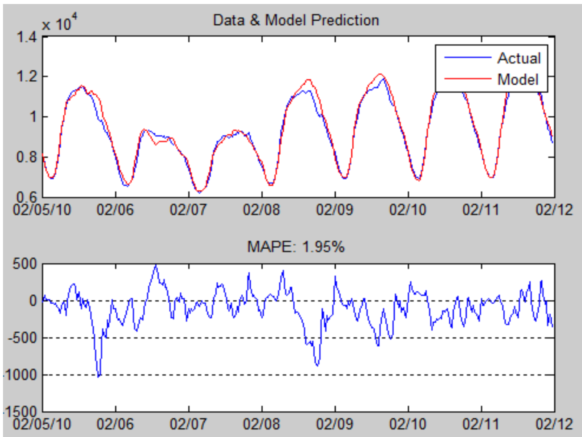


Fig. 8 Comparison between actual load & predicted load weekly

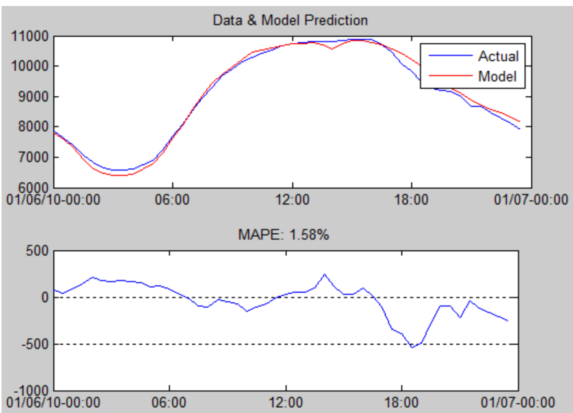


Fig. 9 Comparison between actual load & predicted load daily

By observing the hourly mean error shown in Figure 9, we can see that the most significant errors occur at the turning points of the forecast load curve. This coincidence may suggest that additional information on the form of the curve should be used to improve forecasts and prevent the most serious errors.

In order to evaluate the performance of the load forecasting model, the mean absolute percentage error (MAPE) and the root mean square errors (RMSE) are frequently considered to measure the accuracy between values estimated and predicted by a model or an estimator and the values actually observed.

The MAPE and RMSE are defined respectively as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{10}$$

where y_t is the actual value and $\widehat{y_t}$ is the estimated or forecasted value. In the forecasting period, a MAPE of 2.98% and an RMSE of 62.61MW were obtained in forecasting, which is better than the MAPE of 3.56% and RMSE of 72.95 MW obtained in the ANN method. The results are compared with the conventional method of autoregressive moving average (ARMA) method as shown in Table 3.

Table 3 Different Time step Forecasting Comparison

Time Period	ANN method		ARMA method	
	RMSE	MAPE	RMSE	MAPE
One week	63.61MW	2.89%	72.95MW	3.56%
One day	32.62MW	1.58%	40.53MW	2.29%

6. Conclusions

An ANN-based model was proposed in this paper for short-term load forecasting in disaggregated, microgrid-sized power systems by incorporating back-propagation algorithm. For such purpose, relevant input variables were selected in order to improve the accuracy of forecasting, we not only used weather factors but also a seasonal approach. For recognizing the significant weather factors, the proposed model used the correlation coefficient. Temperature and dew point were selected by the result of the correlation analysis. The temperature and dew point interact to adjust the weather weight size, and the weather weight is used to determine the load demand prediction. Thus, the weather weight was differently applied to each season, which has the season's own pattern of electric consumption. As remarked above, forecasting is more complex in a microgrid because of the increased variability of disaggregated load curves. Accurate forecasting in a microgrid will depend on the variables employed and the way they are presented to the ANN. This study also shows numerically that there is a close relationship between forecast errors and the number of training patterns used; thus, it is necessary to carefully select the training data to be employed with the system. This demonstration is backed up by a detailed database containing real information of load curves disaggregated up to microgrid level running for the future.

감사의 글

이 논문은 한국전력공사 지원에 의하여 전력연구원의 주관으로 수행된 과제(R16DA11)의 연구 결과입니다

References

[1] J. W. Taylor, P. E. McSharry, "Short-term load forecasting methods: An evaluation based on European data," IEEE Transaction on Power System, no. 22, pp. 2213-2219, 2008.

[2] M. Shelke1, P. D. Thakare, "Short Term Load Forecasting by Using Data Mining Techniques," Int. Journal of Science and Research, ISSN (Online): 2319-7064, vol. 3(9), 2014, pp. 1363-1367

[3] Cheol-Hong Kim, Bon-Gil Koo, JuneHo Park, "Short-term Electric Load Forecasting Using Data Mining Technique," J Electr Eng Technol, vol. 7(6), pp. 807-813, 2012

[4] K. Y. Lee, J. H. Park, "Short-term load forecasting using an artificial neural network," Transactions of Power Systems, vol. 7, no. 1, February, 1992.

[5] M.W. Xiao, B.X. Min, M. Shun, "Short-term load forecasting with artificial neural network and fuzzy logic," Internat conference on power system technology, vol. 2, pp 1101-1104, 2002.

[6] A. Jain, B. Satish, "Clustering based Short Term Load Forecasting using Support Vector Machines," Bucharest Power Tech Conference, June 2009.

[7] Kim, H. M.; Kinoshita, T.; Shin, M. C. "A multiagent system for autonomous operation of islanded microgrids based on a power market environment," Energies, 2010, 3, 1972-1990.

[8] Kim, H. M.; Lim, Y.; Kinoshita, T. "An intelligent multiagent system for autonomous microgrid operation," Energies 2012, 5, 3347-3362.

[9] Xiao, Z.; Li, T.; Huang, M.; Shi, J.; Yang, J.; Yu, J.; Wu, W. "Hierarchical MAS based control strategy for microgrid," Energies 2010, 2, 1622-1638.

[10] A. K. Suykens, T. V. Gestel, J. D. Brabanter, B. D. Moor, J. Vandewalle, "Least Squares Support Vector Machines," World Scientific, Singapore, 2002.

[11] N. Kandil, R. Wamkeue, M. Saad, S.Georges, "An effective approach for short term load forecasting using artificial neural network," Electrical Power and Energy Systems, no. 28, pp. 525-530, 2006.

[12] D. Niu, Y. Wang, D. Dash Wub, "Power load forecasting using support vector machine and ant colony optimization," Expert Systems with Applications, no. 37, pp. 2531-2539, 2010.

[13] D. C. Park, et. el "Electric load forecasting using an artificial neural network, IEEE Trans. Power System, 6 1991, pp. 442-449

[14] Ronak K Patel, Ankit V Gajjar, "Short term load forecasting using artificial neural network technique," International Jouranl for Tech. Research Eng'g, vol. 1, no. 9, 2014, pp. 736-740.

[15] L. Hernandez, C. Baladrón, J. M. Aguiar, Belén Carro, "Short-Term Load Forecasting for Microgrids Based on Artificial Neural Networks," Journal of Energies, vol. 6, 2013, ISSN 1996-1073, pp. 1385-1408

[16] D. Kown, M. Kim, C. Hong, S. Cho, "Short Term Load Forecasting based on BPL Neural Network with Weather Factors," Int. Journal of Multimedia and Ubiquitous, vol. 9, no.1, 2014, pp. 415-424

저 자 소 개

정 대 원 (Dae-Won Chung)

1957년 8월 6일생. 1983년 부산대 공대 전기공학과 학사. 1996년 충남대 대학원 전기공학과 석사. 1999년 동 대학원 전기공학과 박사. 1982년~1990년 한국전력기술 선임기술원. 1990년~1997년 한국원자력연구소 선임연구원. 1997년 3월~현재 호남대학교 공대 전기공학과 교수
관심분야: 메카트로닉스, 신재생에너지변환, 계측제어시스템,
Tel: 062-940-5494, E-mail: dwchung@honam.ac.kr

양 승 학 (Seung-Hak Yang)
1982년 전남대 공대 계측제어공학과 학사. 1984년 전남대 대학원 전기공학과 석사. 1993년 東京大學 대학원 전기공학과 박사. 1993년~1994년 東京大學 생산기술연구소 특별연구원. 1995년 3월~현재 호남대 공대 전기공학과 교수
관심분야: 전력변환시스템, 배터리 충방전 제어시스템 등
Tel: 062-940-5708, E-mail: yangsh@honam.ac.kr

유 용 민 (Yong-Min You)
1976년 8월 28일생. 2002년 한양대 전자공학과 학사. 2004년 동 대학원 전자전기제어계측공학과 석사. 2004년~2006년 모아텍 주임연구원. 2006년~2009년 삼성전자 선임연구원. 2013년 한양대 대학원 전자전기제어계측공학과 박사. 2013년~2014년 LG전자 책임연구원. 2014년 3월~현재 호남대학교 미래자동차공학부 조교수
관심분야: 전기기기, 친환경자동차, 신재생에너지, 에너지변환,
Tel: 062-940-5499, E-mail: ym.you@honam.ac.kr

윤 근 영 (Keun-Young Yoon)
1977년 9월 20일생. 2003년 한양대 전자컴퓨터공학부 학사. 2005년 동 대학원 전자전기제어계측공학과 석사. 2008년~2016년 삼성전자 책임연구원. 2016년 한양대 대학원 메카트로닉스공학과 박사. 2016년 8월~현재 호남대학교 전기공학과 조교수
관심분야: 전기기기, 신재생에너지, 에너지변환
Tel: 062-940-5489, E-mail: ky.yoon@honam.ac.kr