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Forecasting Short-term Electricity Demand in Residential Sector Based on Support Vector Regression and Fuzzy-rough Feature Selection with Particle Swarm Optimization

Hyojoo Son[a], Changwan Kim[a]*

[a]*Department of Arcitectural Engineeirng, Chung-Ang University, 84 Heukseok-ro, Dongjan-gu, Seoul, Korea*

Abstract

The aim of this study is to provide a precise model for one-month-ahead forecast of electricity demand in residential sector. In this study, a total of 20 influential variables are taken into account including monthly electricity consumption, 14 weather variables, and 5 social variables. Based on support vector regression and fuzzy-rough feature selection with particle swarm optimization algorithms, the proposed method established a model with variables that relate to the forecast without ignoring some of these variables one may inevitably lead to forecasting errors. The proposed forecasting model was validated using historical data from South Korea. Its time period was from January 1991 to December 2012. The first 240 months were used for training and the remaining 24 for testing. The performance was evaluated using MAPE, MAE, RMSE, MBE, and UPA values. Furthermore, it was compared with that obtained from the artificial neural network, auto-regressive integrated moving average, multiple linear regression models, and the methods proposed in the previous studies, and found superior for every performance measure considered in this study. The proposed method has an advantage over the previous methods because it automatically determines appropriate and necessary variables for a reliable forecast. It is expected that the proposed model can contribute to more accurate forecasting of short-term electricity demand in residential sector. The ability to accurately forecast short-term electricity demand can assist power system operators and market participants in ensuring sustainable electricity planning decisions and secure electricity supply to the consumers.

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Keywords: Feature selection; Forecasting; Residential sector; Short-term electricity demand; Support vector regression

* Corresponding author. Tel.: +82-2-825-5726; fax: +82-2-812-4150.
E-mail address: changwan@cau.ac.kr

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1. Introduction

Short-term electricity demand forecasting plays a significant role in power system planning, including economic scheduling of generating capacity and scheduling of fuel purchases, and power system management [1–8]. It is especially obvious that accurate electricity forecasting has great importance to the residential sector, a major contributor to the peak loads in most electricity systems. Overestimating electricity demands misleads planners and wastes resources with expensive expansion plans. Such overestimation also increases operating costs, since electricity cannot be stored on a large scale unlike other energy sources [9,10]. But underestimation of electricity demands will result in failures and shortages [3]. Nevertheless, short-term electricity demand forecasting in the residential sector is a complex problem because its rise and fluctuation is caused by the difference in demand from month to month. In addition, the consumption is influenced by many nonlinear variables, such as weather conditions, economics, and demographics [11–14,3,15,7].

Several research studies have been conducted over the last decades to explore this complex problem of monthly electricity demand forecasting by means of multivariate time series analysis [16–32,7,33–35]. Several studies have assumed that the input and output series are stationary and applied statistical models [16,36,17,21–23,25,30,7]. However, real monthly electricity demand series as well as variables that may influence the electricity demand series have found to be non-stationary characteristic [17]. When one or more of the input and output series are have non-stationary characteristic, it is necessary to consider the sophisticated models which are capable of describing the nonlinear input and output series. In order to solve nonlinear time series problems, most research studies applied auto-regressive integrated moving average model [17,20] and artificial neural network model-based approaches [18,19,24,26,28,29,31–34]. The accuracy of the resulting models has ranged from 1.42% [34] to 10.98% [18] in terms of mean absolute percentage error. However, it is difficult to say whether these models have been sufficiently validated because the evaluation periods of the most research studies were within about ten years [18–20,29,31–34]. In addition, most of the previous studies have assumed that certain inputs among various weather variables and social variables have impact on the electricity demand series and fed these inputs to develop their models. Although some of selected variables may inevitably lead to forecasting errors, to our knowledge, there have been no research studies examining the method that can determine appropriate and necessary variables for a reliable forecast of monthly electricity demand in residential sector.

The aim of this study is to provide a precise model for one-month-ahead forecast of electricity demand in residential sector. Based on support vector regression and fuzzy-rough feature selection with particle swarm optimization algorithms, the proposed method automatically develops a forecasting model with variables that relate to the electricity demand series without ignoring some of these variables one may inevitably lead to forecasting errors. To evaluate the forecasting performance of the proposed method, we performed a comprehensive comparison of the prediction performance of the proposed method versus that of the artificial neural network, auto-regressive integrated moving average, multiple linear regression models, and the methods proposed in the previous studies. A data set covers the period from January 1991 to December 2012 was collected from South Korea and used for training and testing experiments. In Section 2, we present some materials on the proposed methodology. In Section 3, we described the data set and pre-processing. In Section 4, we present a discussion and analysis of the experimental results. Section 5 contains conclusions and suggestions for future research.

2. Methodology

2.1. Analysis steps

This study was conducted according to the procedure outlined in Fig. 1. In Step 1, support vector regression (SVR) and fuzzy-rough feature selection with particle swarm optimization (PSO) algorithms were applied to select the most relevant variables from the 19 input variables. As a result, the number of multi-dimensional input variables was reduced. In Step 2, a forecasting model was developed by training the support vector regression model with the variables selected in the first step. In Step 3, the artificial neural network (ANN), auto-regressive integrated moving average (ARIMA), multiple linear regression (MLR) models, and the methods proposed in the previous studies were trained. In Step 4, the forecasting performance of the ten models was compared.

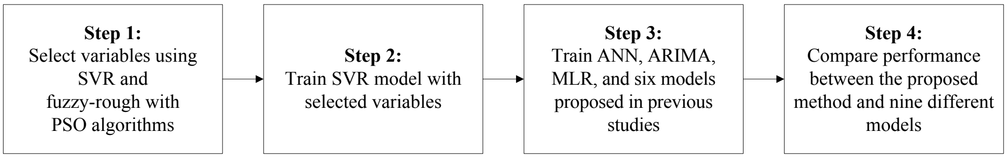

Fig. 1. Outline of procedure of the proposed method.

2.2. Support vector regression (SVR) and Fuzzy-rough feature selection with particle swarm optimization (PSO)

Monthly electricity demand has a cyclic trend caused by the difference in demand from month to month and season to season. Although the SVR model is capable of dealing with cyclic trend of time series, the application of SVR model has not yet been explored for the problem of electricity demand forecasting in residential sector [37]. In real applications in time series prediction, SVR algorithm has received extensive attention as a learning algorithm offering many theoretical advantages [38,39]. To build SVR-based forecasting model, feature selection and proper model parameter setting can improve the forecasting capability of SVR. In this study, under SVR formulation, fuzzy-rough feature selection method [40] was adopted and modified to improve the forecasting capability of trained SVR model by searching and finding the optimal variable subset. This method is based on PSO algorithm which utilized fuzzy dependency degree as evaluation measure. The algorithm initiates by generating N numbers of particles randomly. Each particle indicates a subset of input variables. The best particles are obtained in all iterations and are called as global bests. Then, personal best of each particle is obtained and the best immediate neighbors for each particle are obtained. The velocity of the particle is updated and the position update rule is formulated. The fitness of the particle is calculated and the termination condition is checked. Details of the fuzzy-rough feature selection method can be found in Cornelis and Gensen [41], Cornelis et al. [42], and Jensen and Shen [43] as well as details of the PSO algorithm can be found in Wang et al. [44] and Wang et al. [45].

The variables obtained by the SVR and fuzzy-rough with particle swarm optimization algorithms in the feature selection step are passed to train SVR model for validation. With an RBF kernel, there are two parameters to be determined in the SVR model: the regularization parameter, C and the kernel parameter, λ. In order to find the best (C, λ) values, this study performed the "grid-search" approach proposed by Hsu et al. [46] and Wang et al. [47]. The grid search was performed as follows [46]: First, we selected a grid space with C (10^{-2}, 10^{-1}, …, 10^{4}, 10^{5}) and λ (10^{-5}, 10^{-4}, …, 10^{0}, 10^{1}). Then, for each pair of C and λ in this space, the RMSE was calculated for the test period. Finally, the pair (C, λ) that yielded the smallest value of the RMSE was chosen, and that pair was used.

3. Data Set and Pre-processing

There are 20 related variables (as shown in Table 1) including monthly electricity consumption, 14 weather variables, and 5 social variables (economic and demographic factors). The comprehensive list was developed from the literature [16–20,23–26,29–34]. The time period of data collection was January 1991 to December 2012. In this study, the monthly residential electricity consumption series and variables that may influence the electricity demand are collected from the statistics published by the Korea Meteorological Administration, Korean Statistical Information System, and Korea Energy Statistics Information System. In South Korea, monthly weather data was obtained from nine regional representative monitoring stations. Each monitoring station was associated with a climate region, and these climate regions represent areas of similar climate, and are therefore somewhat arbitrary. After data collection for 14 weather variables from each monitoring station, these 14 variables were calculated by population-weighted average of the nine regions they represent. The reason why population has been selected as weighting factor is that climate influences the electric consumption through the response of people to weather. That is, depending on the coldness, or heat, of weather, people will increase or decrease the use of electric heating appliances or air conditioners. Thus, the higher the population, the higher the influence of weather conditions in electricity demand [12]. In other words, regional electricity demand is highly correlated with population [48]. Summary statistics are presented in Table 1.

Table 1. Summary statistics for the residential electricity consumption and 19 variables.

No.	Variable name (Unit)	Mean	Std. deviation	Minimum	Maximum
1	Electricity consumption (MWh)	3,478,541.87	1,167,190.45	1,492,690.00	6,256,403.00
2*	**Mean temperature (°C)**	**13.40**	**9.11**	**-4.95**	**28.64**
3*	**Maximum temperature (°C)**	**18.20**	**8.80**	**0.46**	**33.31**
4*	Minimum temperature (°C)	7.83	9.44	-9.84	23.77
5*	Relative humidity (%)	63.47	8.50	45.04	82.66
6*	**Wind speed (m/s)**	**2.44**	**0.31**	**1.67**	**3.26**
7*	Rainfall (mm)	120.79	140.89	3.22	804.15
8*	**Daylight time (hr)**	**175.71**	**36.97**	**55.88**	**256.73**
9*	**Global solar radiation (0.01MJ/m^2)**	**38,151.02**	**11,000.99**	**16,889.65**	**63,613.40**
10*	**Cooling degree days (degree-days)**	**10.47**	**24.46**	**0.00**	**147.09**
11*	Heating degree days (degree-days)	201.07	211.24	0.00	714.58
12*	**Total number of cooling degree days (degree-days)**	**10.29**	**24.49**	**0.00**	**147.09**
13*	Total number of heating degree days (degree-days)	200.88	211.42	0.00	714.58
14*	**Vapor pressure (0.1hPa)**	**119.91**	**75.94**	**22.04**	**291.87**
15*	Air pressure (0.1hPa)	10,161.31	64.81	10,047.08	10,271.27
16	Real gross domestic product (billions of won)	191,076.33	44,693.43	103,141.20	273,719.10
17	Industrial production index	238.98	105.79	85.32	446.24
18	Population (million)	47,766.42	2,042.62	43,296.00	50,948.27
19	**Consumer price index**	**165.60**	**36.28**	**100.00**	**228.97**
20	**Real electricity price (won/kWh)**	**47.32**	**5.88**	**38.10**	**69.53**

Note. * indicates that it was calculated by population-weighted average of the nine regions they represent. Monthly data were interpolated assuming smooth changes from the quarterly data (real gross domestic product and population).

4. Results and Discussion

The performance of the proposed method was evaluated using the collected data set. The results obtained by the proposed method were compared with the results obtained by the artificial neural network, auto-regressive integrated moving average, multiple linear regression models, and the methods proposed in the previous studies. The experimental results are summarized in Table 2 and illustrated in Fig. 2. The first step of the procedure consisted of selecting the most relevant subset of variables from the set of 19 candidate variables. Based on support vector regression and fuzzy-rough feature selection with particle swarm optimization algorithms, 11 variables including monthly electricity consumption, 8 weather variables, and 2 social variables were utilized for modeling the monthly electricity consumption. Shaded rows in bold text in Table 1 indicate the selected variables by the proposed method for modeling the monthly electricity demand.

The performance was evaluated using mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), mean bias error (MBE), and unpaired peak accuracy (UPA) values. MAE and RMSE values allow a term-by-term comparison of the actual deviation between the forecasted value and actual value. Since the MAE and the RMSE are based on absolute errors, there is no absolute criterion for a "good" value for either of them. All that can be inferred from them is that the smaller the value of MAE or RMSE, the closer the predicted values to the actual values. The MAPE, however, is scale independent, since it is based on relative errors; hence, it is more meaningful [49]. Positive and negative values of MBE represent overestimated and underestimated forecasted values, with a small value of MBE being desirable. The UPA value gives a measure of model's ability to capture peak demand, but does not pair the model forecasts with actual value in time or space. The performance statistics of the proposed model and nine different models are given in Table 3. The proposed method yields the highest performance among the ten models in terms of MAPE, MAE, RMSE, and MBE values. At the peak point, the proposed method was ranked in the second position, yielding -5.89 in terms of UPA value. It means that the residential electricity demand at the peak point was underestimated by the proposed method with 5.89% error.

Table 2. Comparison of ten different models.

Method	MAPE	MAE	RMSE	MBE	UPA
Proposed method	**2.13**	**113,870.67**	**149,287.54**	**45,695.11**	-5.89
Artificial neural network (ANN)	9.92	522,503.25	633,073.65	500,754.67	14.03
Auto-regressive integrated moving average (ARIMA)	4.71	242,005.30	261,671.62	224,571.82	**-2.57**
Multiple linear regression (MLR)	7.15	361,170.52	426,779.00	300,159.62	-7.14
Proposed by Islam and Al-Alawi (1997)	3.96	203,109.63	241,167.57	160,884.52	-6.88
Proposed by Hor et al. (2005) – Model 1	2.78	152,485.53	220,244.03	-95,728.85	-12.05
Proposed by Hor et al. (2005) – Model 2	3.30	175,170.65	231,332.24	-131.75	-9.51
Proposed by Hor et al. (2005) – Model 3	4.53	244,468.27	301,318.18	-229,422.22	-14.06
Proposed by Pao et al. (2006)	6.09	331,167.88	417,682.95	-331,167.88	-19.61
Proposed by Bunnoon et al. (2010)	7.70	411,642.53	520,294.26	-352,916.51	-14.83

Note. The values were rounded to four decimals places.

Graphical comparison of the actual values (blue line) to the forecasted values (red line) by the proposed method from January 2011 to December 2012 is presented in Fig. 2. The time series of residential electricity consumption is also plotted in Fig. 2. The series presents a complex monthly and seasonal trends and strong fluctuations. Especially, these data exhibit a significant and persistent upward trend until the end of 2012, mainly associated with the economic and demographic growth in the country. In addition, a cyclic annual pattern, which is correlated with the global climate changes throughout the year, is superimposed over these monthly and seasonal trends. The amplitude of the collected values also reflects the different number of days, working days, and holidays included in each month. The forecasted values (red line) by the proposed model are closer to the actual values. From the results, one could conclude that the forecasted values show relatively good agreement with the actual values and that the proposed method is feasible and reliable.

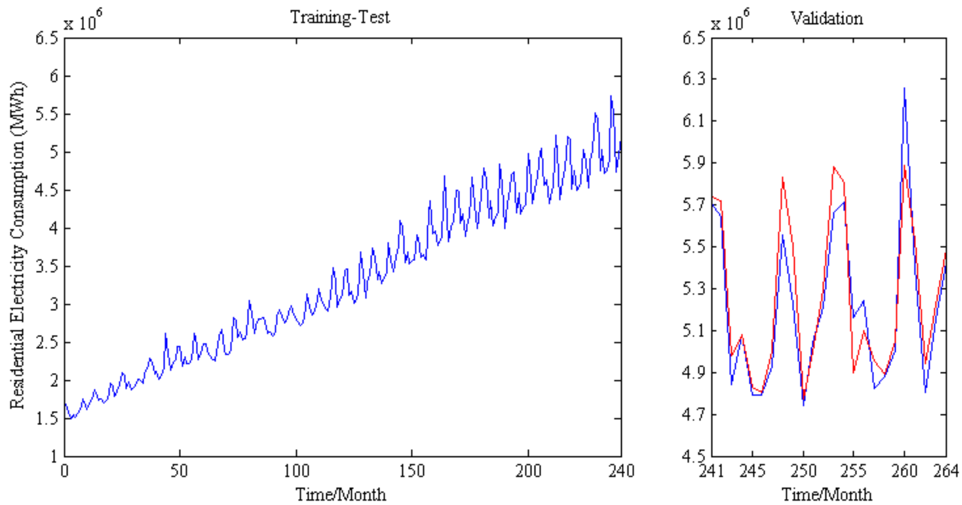

Fig. 2. Forecasting results using the proposed method.

5. Conclusion

This study proposed a method to provide a precise model for one-month-ahead forecast of electricity demand in residential sector. The support vector regression and fuzzy-rough feature selection with particle swarm optimization algorithms identified ten variables from a set of 19 candidate variables that may influence the electricity demand series and used to construct forecasting model. With fewer input variables, the proposed method was able to more accurately forecast the electricity demand in residential sector. Several interesting findings have been made in this study. Prior to this study there was relatively little understanding of feature selection method that significantly contribute the capability of electricity demand forecasting in residential sector. This study proposed the method that can identify relevant variables for forecasting the electricity demand in residential sector with comprehensive consideration of variables that may influence the electricity demand series. In addition, the empirical comparison of the forecasting capability between the proposed method and the methods proposed in the previous studies confirmed that the proposed method is the best predictor of the monthly electricity demand in residential sector. Moreover, the proposed method has an advantage over the previous methods because it automatically determines appropriate and necessary variables for a reliable forecast. It is expected that the proposed model can contribute to accurate forecasting of short-term electricity demand in residential sector. The ability to accurately forecast short-term electricity demand can assist power system operators and market participants in ensuring sustainable electricity planning decisions and secure electricity supply to the consumers. This highly accurate forecasting method also has great potential for solving other forecasting problems in the construction industry.

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