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Research Paper

Electricity consumption prediction for buildings using multiple adaptive network-based fuzzy inference system models and gray relational analysis

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ABSTRACT

The rise in environmental awareness has increased the significance of controlling and monitoring electricity consumption. The efficiency of power management is directly affected by the accuracy of predicting electricity consumption. It is easy to estimate the electricity consumption if the electricity status is predicted. Therefore, this study proposes a method to predict the electricity consumption of public buildings by using an adaptive network-based fuzzy inference systems (ANFISs) and weather conditions. ANFIS combines the interpretability of fuzzy inference systems and the learning ability of neural networks. Gray relational analysis (GRA) is used to analyze the relationship between weather conditions and electricity consumption. In this study, a multi-ANFISs approach is introduced to estimate the electricity consumption by weather conditions and human activities. An alarm system was also developed using the estimation errors. The results show that the proposed multi-ANFISs achieves a greater performance with less number of parameters, and the GRA can evaluate the magnitude of relation between the factors and a specific output.

1. Introduction

The electricity consumption is increasing with the rising economic growth (Shahbaz et al., 2017; Su, 2019). In the case of an urgent need of excess electricity, the efficiency of power generators drops and they create harmful exhausts. A proper power generation plan can lower the negative impact of these generators. The Taiwan Power Company (TPC) offers public institutions and private enterprises a contract of electricity consumption. According to this contract, the institutions estimate the amount of electricity they will consume during a billing period. If the consumed electricity is in the estimated range, they are rewarded with a lower price per kWh. On the other hand, if the consumed electricity exceeds the estimated range, the institutions pay a higher price per kWh as a penalty. This program lets TPC predict the total electricity and avoid instances of emergency power supply. Thus, this study introduces an adaptive network-based fuzzy inference system (ANFIS) model to estimate the electricity consumption of a building using weather conditions and human activities.

The chosen mathematical model directly affects the accuracy of the prediction of electricity consumption. Various predicting approaches have been proposed in other studies (Deb et al., 2017; Kumar et al., 2013; Tetlow et al., 2015; Xie et al., 2016), for example, random forest (Ahmad et al., 2017), cluster analysis (Deb and Lee, 2018; Hsu, 2015), linear and nonlinear artificial neural network (ANN) (Kumar et al., 2013; Ahmad et al., 2017; Azadeh et al., 2008; Ekici and Aksoy, 2009; Işık and Inallı, 2018; Neto and Fiorelli, 2008; Pao, 2006; Shi et al., 2016; Wong et al., 2010; Ye and Kim, 2018), etc. Table 1 summarizes the input variables for these models. In this study, we adopt a multiple adaptive network-based fuzzy inference system (multi-ANFISs) approach to estimate the electricity consumption, which combines fuzzy inference systems and the structure of neural networks, which means that ANFIS has both learning ability and interpretability. Studies have shown that this can be used for electricity consumption forecasting (Işık and Inallı, 2018; Azadeh et al., 2009).

In this paper, we predict electricity consumption using a simplified and meaningful method using multi-ANFISs. Multiple inputs affect electricity consumption, but the corresponding influence level of each factor is unknown. Therefore, gray relational analysis (GRA) is used to evaluate the correlation between electricity consumption and the input factors. ANFIS is chosen as the relationship between the input variables and the output can be shown by If-Then rules, which are more meaningful than the weights and biases in other machine learning tools. In addition,

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Table 1
Summary of mentioned studies.

Method	Input variables
ANN & Random forest (Ahmad et al., 2017)	Temperature, dew-point temperature, relative humidity, time variables, variables depending on hotel operation
Cluster analysis (Deb and Lee, 2018; Hsu, 2015)	Variables depending on air-conditioning operation, tax value, and other economic indices
ANN4 (Azadeh et al., 2008; Ekici and Aksoy, 2009; Işık and Inallı, 2018; Neto and Fiorelli, 2008; Pao, 2006; Shi et al., 2016; Wong et al., 2010; Ye and Kim, 2018)	Simplified weather conditions, human activities, time series data, economic indices, variables depending on air-conditioning operation and industries, office condition, building material and design
ANFIS (Işık and Inallı, 2018; Azadeh et al., 2009)	Weather conditions, Time series data

the problem considered does not need a deep learning technology. We apply multi-ANFISs in three different states for the building investigated in our study. The inputs are the outside weather conditions, including temperature, precipitation, sunshine duration, solar radiation, cloud covering, and relative humidity. Different ANFIS models are chosen for working days, school days, and holidays in buildings of both public institutions and private enterprises. Finally, we compare the results obtained using our method with the Levenberg–Marquardt back-propagation neural network, single ANFIS model, linear regression, and nonlinear regression. By using multi-ANFISs, we can predict electricity consumption as well as the relationship between the input factors and the output.

This paper is organized as follows: In Section 2, the problem definition and methodologies are introduced. In Section 3, the data used is shown and explained. Section 4 introduces the proposed method and experimental results, and also includes the performance comparison with other methods. Finally, the conclusion is presented according to the experimental results.

Main contributions

1. Discussing the level of influence for different input factors on electricity consumption forecasting. By experiment, GRA can filter important input factors.
2. Using multiple models to solve the binary problem when applying ANFIS.
3. Discussing the relationship between input factors (weather conditions, human activities) and electricity consumption. The effect of human activity is much larger than weather conditions, and thus it is transferred to a criterion for selecting models.
4. Comparison results of each method and the relationship of input factors for electricity consumption generated by multi-ANFISs_GRA, multi-LMBP_GRA, linear regression, nonlinear regression, single ANFIS, and PACF+SAE. Multi-ANFISs_GRA is simpler with an acceptable performance.
5. An alarm system established using predicted error is proposed, which determines the unusual electricity consumption and excludes the special cases initially.

2. Preliminaries

This section introduces the preliminaries, including problem formulation of electricity prediction, adaptive network-based fuzzy inference system (ANFIS), gray relational analysis (GRA), normalization of data, and evaluation indices.

2.1. Prediction of electricity consumption

Electricity consumption is a basis for power companies to calculate electricity bills. It is also used to assess the amount and efficiency of electricity generation. The main consumers of electricity are air conditioners, elevators, computers, etc. Among these devices, air conditioners, known as heating, ventilating, and air conditioning (HVAC), maintain the temperature inside the building by heat exchange with the outside environment, i.e., the required energy depends on the weather conditions. Thus, the amount of electricity consumption of these devices is related to human activities. Here, we investigate the electricity consumption of a public building (Library) using weather conditions and human activities. We choose average temperature, wind speed, precipitation, sunshine duration, solar radiation, cloudiness, and average relative humidity as the inputs of weather conditions, represented by $x_1, x_2, \ldots, x_7$, and use the human activity to select a suitable prediction model. The highest frequency of people entering and leaving the library are students and the officers working inside the building. Therefore, we simplify human activities into two conditions, working day and school day conditions, which are represented by x_8 and x_9, respectively The output of the predicted electricity consumption (y) is represented as

$$y = f(x_1, \ldots, x_9). \tag{1}$$

2.2. Gray Relational Analysis

Gray relational analysis (GRA) is used to solve the tuning operations with multiple performance characteristics (Ping Zhang et al., 2013). It has three steps, data normalization, relational coefficient computation, and correlation calculation.

First, we use different normalizing methods on each factor since the relationship between each factor and the output is different. In the following, $x_i(k)$ and $x_o(k)$ denote the input and output, respectively. We normalize the dataset as follows:

$$X_i(k) = \frac{x_i(k) - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{2}$$

$$X_i(k) = \frac{\max(x_i) - x_i(k)}{\max(x_i) - \min(x_i)} \tag{3}$$

$$X_o(k) = \frac{x_o(k) - \min(x_o)}{\max(x_o) - \min(x_o)}. \tag{4}$$

For temperature, precipitation, sunshine duration, solar radiation and relative humidity, we use Eq. (2) to normalize, as these factors and electricity consumption are positively correlated according to our study. For wind speed and cloud cover, we use Eq. (3) to normalize. Eq. (4) shows the corresponding normalization for output variable.

And then the gray relational coefficient (GRC) is obtained by

$$\Delta X_i(k) = |X_o(k) - X_i(k)|. \tag{5}$$

Subsequently, we compute the GRC between output and inputs by

$$\zeta_i(k) = \frac{\min \Delta X_i(k) + \xi max(\Delta X_i(k))}{\Delta X_i(k) + \xi max(\Delta X_i(k))}, \tag{6}$$

where ζ is the identification coefficient. $0 \le \zeta \le 1$. $\zeta = 0.5463$ has the best resolution ability according to some studies. In this study, we use $\zeta = 0.1, 0.2, \ldots, 0.9, 1$ and computed the average of γ_i in the final step of GRA using a different ζ.

Finally, the gray relational grade (GRG) is calculated. At this stage, we have the average of ζ_i,

$$\gamma_i = \frac{\sum_{k=1}^{n} \zeta_i(k)}{n}, \tag{7}$$

where γ_i is called GRG that shows the influence level of each factor.

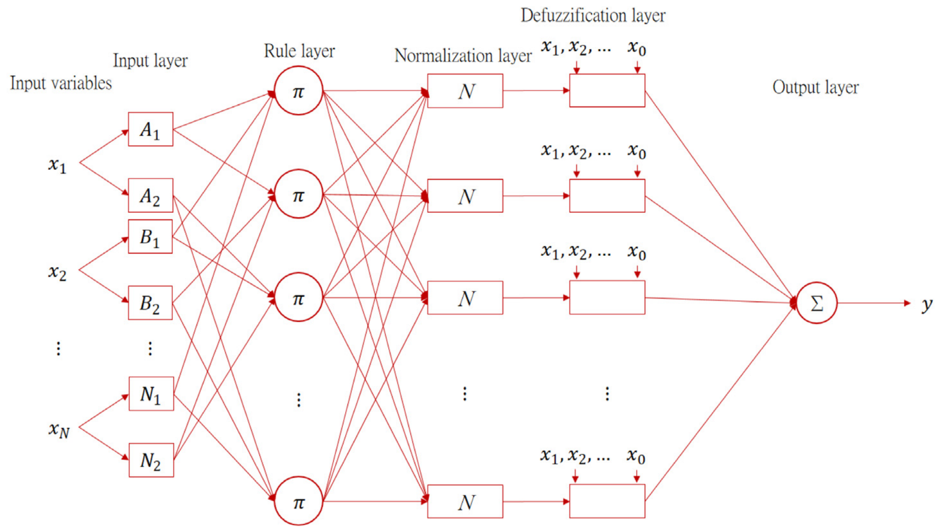


Fig. 1. Structure of ANFIS.

2.3. Adaptive Network-based Fuzzy Inference System (ANFIS)

We assume that the relationship between the input variables and the output is formulated as in Eq. (1) that is established by the ANFIS. Fuzzy inference system is based on the way people make decisions on imprecise and non-numerical information. It uses If-Then rules that are defined by a dataset or the user to make final decisions to reach control purposes. ANFIS combines fuzzy inference systems and neural network (Hsu, 2015). The structure of the first-order Sugeno-type ANFIS (TSK) is shown in Fig. 1.

From input variables, the corresponding membership values of input variables are computed by

$$O_{1,ij} = \mu_j(x_i) = exp(-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}),$$
$$i = 1, 2, \ldots, N; j = 1, 2, \ldots, M \tag{8}$$

where m_{ij}, σ_{ij} are the center and the width of a Gaussian membership function, respectively; x_i denote the weather condition inputs; M denotes the fuzzy partition number.

The second layer is the rule layer. The firing strength is calculated by the Mamdani t-norm product

$$O_{2,p} = \prod_{i=1}^{N} \mu_j(x_i) = w_p, j = 1, 2, \ldots, M; p = 1, 2, \ldots, P. \tag{9}$$

Subsequently, the normalization operation is applied

$$O_{3,p} = \frac{w_p}{\sum_{p=1}^{P} w_p} = \overline{w_p}. \tag{10}$$

The output of the defuzzification layer is

$$O_{4,p} = \overline{w_p} f_p = \overline{w_p}\left(\sum_{i=0}^{N} r_{pi} x_i\right), x_o = 1 \tag{11}$$

where r_{pi} is a parameter of the first order Sugeno model. Finally, the output of ANFIS is

$$O_{5,p} = \sum_{p=1}^{P} \overline{w_p} f_p = \frac{\sum_{p=1}^{P} w_p f_p}{\sum_{p=1}^{P} w_p}. \tag{12}$$

In the training process of ANFIS, the training algorithm will adjust the width and center of membership functions according to the If-Then rules.

In this study, the ANFIS is used to predict the electricity consumption using weather conditions and it is implemented by MATLAB R2014a. For each structure, we made three attempts and computed the average error.

Before training and predicting, the data is normalized by

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{13}$$

where x' is the normalization value of data. In this study, we use mean squared error (MSE) and mean absolute percentage error (MAPE) to evaluate the performance of models. MSE is the average of the squared error of all data computed by

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(\widehat{y_n} - y_n)^2, \tag{14}$$

where $\widehat{y_n}$ is the normalized output of the model and y_n is the normalized target. MAPE is a typical percentage error. The error in percentage can give a more identical criterion to compare the models. MAPE can be computed by

$$MAPE = \frac{1}{N}\sum_{n=1}^{N}\frac{|\widehat{y_n} - y_n|}{y_n}. \tag{15}$$

3. Dataset introduction

The corresponding electricity consumption data used in this paper is the electricity consumption of the library of Providence University, Taichung, Taiwan. Weather condition data is obtained from the Wuqi District weather station, Taichung, listed in Table 2. Data from December 2017 to November 2018 is set to be the training data, and from December 2018 to February 18, 2019 is the testing data. The training data is shuffled before every training. From Table 2, there are nine variables considered in this study. The constraints of the training dataset are listed in Table 3.

4. Electricity prediction using multi-ANFISs_GRA

According to our observations, the electricity consumptions of different human activities (working day and school day conditions) are different even if the weather conditions are similar. Table 2 (2018/04/01∼2018/04/03) lists three days having similar weather conditions, for which different combinations of working day and school day conditions result in different electricity consumption. Thus, working days and school days are considered as

Table 2
Part of the dataset for this study (2017/12/01∼2017/12/10) and (2018/04/01∼2018/04/03).

Date	Avg. Temp. (°C)	Wind speed (m/s)	Precip. (mm)	Sunshine duration (h)	Solar radiation (MJ/m^2)	Cloud	Avg. relative humidity (%)	Work	School	Elect. consume (kWh)
2017/12/1	19.7	10	0	1	8.33	8.3	78	1	1	4588
2017/12/2	20.2	8.4	0	1.1	8.57	8.5	81	1	0	2877
2017/12/3	20.7	8.5	0	3.3	9.19	6.5	80	1	0	2861
2017/12/4	19.6	9.4	0	9.5	14.23	0	69	1	1	4509
2017/12/5	17.2	8	0	5.5	10.35	4.5	62	1	1	4461
2017/12/6	16.4	4.5	0.5	0.3	5.17	9.5	72	1	1	4319
2017/12/7	16.9	4.7	2	0.1	4.65	9.5	85	1	1	4222
2017/12/8	14.8	9.5	1.5	0	5.11	10	69	1	1	3788
2017/12/9	14.5	3.8	2	1.1	5.76	9	80	1	0	2533
2017/12/10	17.3	4.4	0	8.7	12.85	2.3	79	1	0	2641
					…					
2018/4/1	24.1	2.7	0	5.8	17.44	5.5	73	1	0	3225
2018/4/2	23.5	1.9	0	6.7	19.28	5	77	1	1	4401
2018/4/3	23.9	2.1	0	7.2	21.19	4.8	71	0	0	1347

Table 3
Constraints for all variables.

	Avg. Temp. (°C)	Wind speed (m/s)	Precip. (mm)	Sunshine duration (h)	Solar radiation (MJ/m^2)	Cloud	Avg. relative humidity (%)	Work	School	Elect. Consume (kWh)
Max	30.8	11.2	126	12.4	27.51	10	96	1	1	8645
Min	8.9	1.6	0	0	0.74	0	46	0	0	964

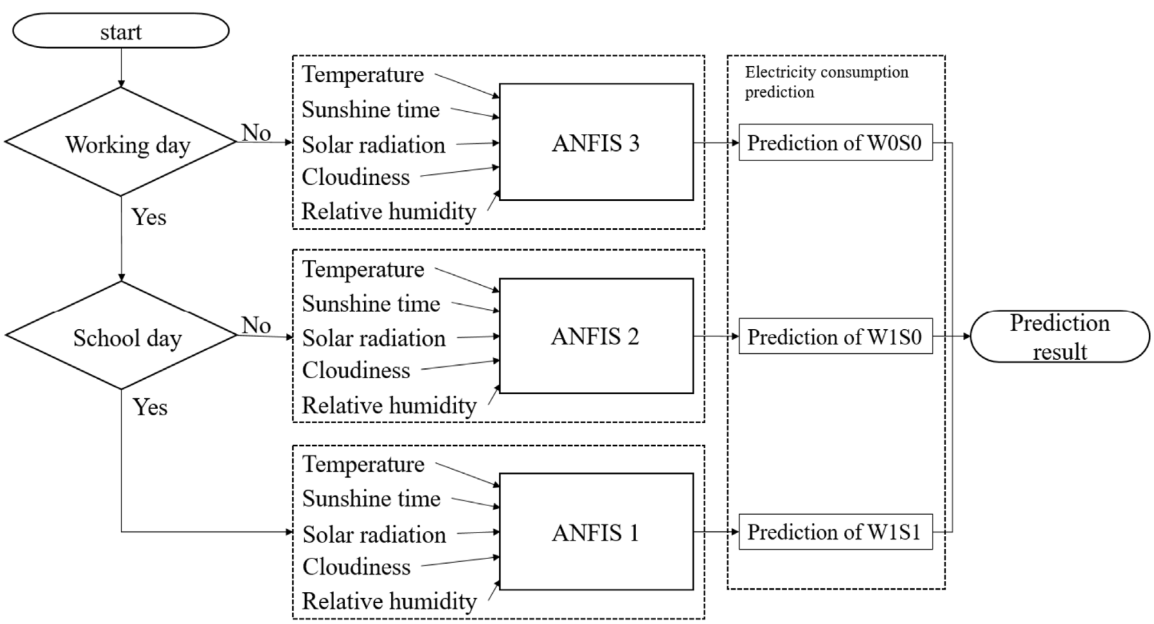


Fig. 2. Prediction scheme using Multi-ANFISs.

the main parameters for selecting the prediction ANFIS model. The binary coding of working day and school day dates are not suitable to use with ANFIS directly, and hence the relationship between each factor is adjusted to change the binary problem into a continuous distribution. Therefore, the two parameters (working date and school date) are used to select the corresponding model and the other factors are the inputs of the multi-ANFISs. The proposed multi-ANFISs predicted scheme is shown in Fig. 2. Using this, we can improve the rationality of ANFIS when encountering a binary problem.

In general, more inputs result in complexity and a higher computation effort. Hence, we need to select the main factors and ignore the ones that are less important. We adopt the GRA to evaluate the influence level of the various weather conditions. As described in Section 2.2, the GRC results of GRA shows the influence of factors. The GRG values calculated using GRC results contains the complete information about how each factor affects the whole dataset. The dataset is divided into three sets, "W1S1" is the dataset for both working day and school day, "W1S0" is dataset for working day but not school day, and "W0S0" is dataset for a holiday. We use three ANFIS models for three different situations. For each model, we use the weather conditions with the top five GRG values as inputs. The entire process of the proposed method can be comprehended as: human activities determine the basic level of electricity consumption and weather conditions are used for tuning the final value. The equation of our problem formulation can be rewritten as

$$\begin{cases} if\ x_8 = 1\ and\ x_9 = 1, y = f_1(X_1, X_2, \ldots, X_5) \\ if\ x_8 = 1\ and\ x_9 = 0, y = f_2(X_1, X_2, \ldots, X_5) \\ \quad if\ x_8 = 0, \qquad y = f_3(X_1, X_2, \ldots, X_5), \end{cases} \tag{16}$$

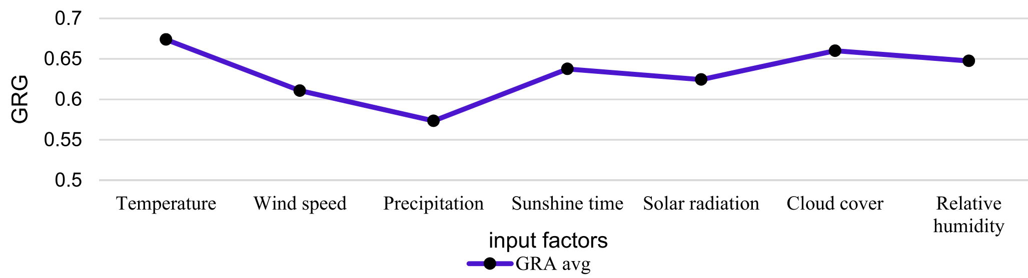
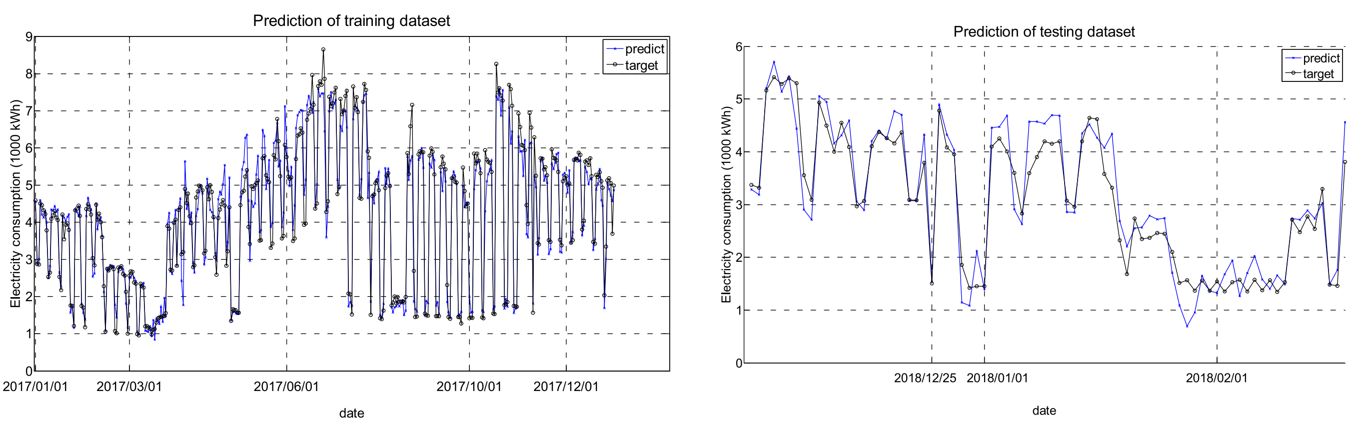


Fig. 3. GRG of weather conditions.



(a) (b)

Fig. 4. Prediction results using structure 1.

Table 4
Performance of the proposed multi-ANFISs_GRA scheme.

Parameters of MF structure	Number of membership functions					Training error	Testing MSE	Epochs (each ANFIS)
	Temp.	Sunshine duration	Solar radiation	Cloud	Relative humidity			
Structure 1	**2**	**2**	**2**	**2**	**2**	**W1S1: 0.0604** **W1S0: 0.0543** **W0S0: 0.0389**	**0.0273**	**500**
Structure 2	3	2	2	2	2	W1S1: 0.0582 W1S0: 0.0535 W0S0: 0.0287	0.0654	1000
Structure 3	2	3	3	2	2	W1S1: 0.0587 W1S0: 0.0527 W0S0: 0.0282	0.035	1000
Structure 4	2	2	2	3	2	W1S1: 0.061 W1S0: 0.05 W0S0: 0.029	0.0793	1000
Structure 5	2	2	2	2	3	W1S1: 0.0579 W1S0: 0.0526 W0S0: 0.0344	0.0513	1000

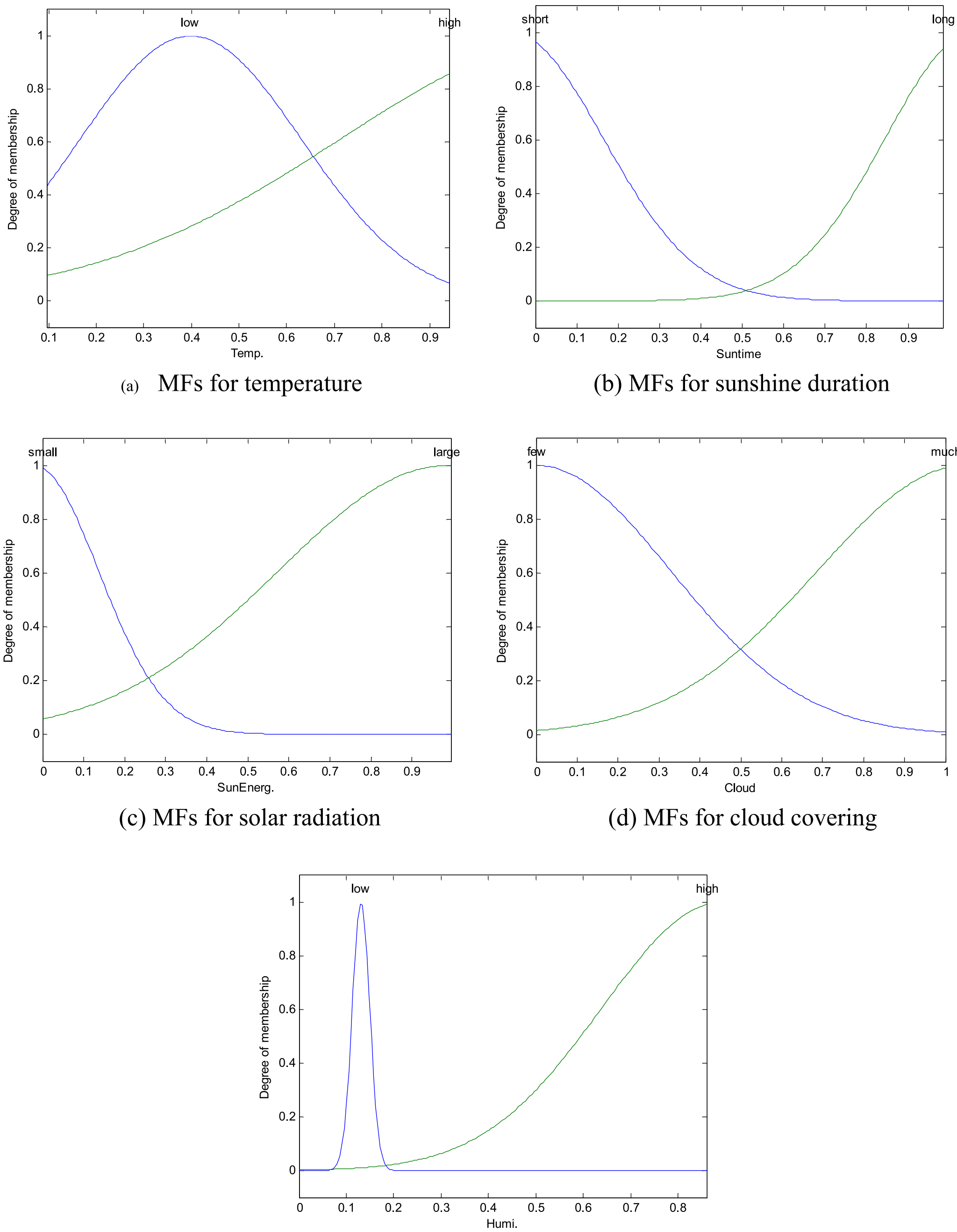
where $X_1, X_2, \ldots, X_5$ are the top five input factors, x_8, x_9 are the working day and school day conditions.

5. Experimental results and discussions

This section introduces several experimental results to show the effectiveness and performance of our approach, including the comparison results on applying GRA to weather conditions for electricity consumption, comparison results using multi-ANFISs and single ANFIS, prediction using the LM-BP neural network, and alarm for abnormal situations. According to Table 1, there are very few studies that have used weather conditions as input variables. Moreover, the results of Azadeh et al. (2008), Işık and Inallı (2018) and Deb and Lee (2018) using weather conditions did not introduce the relational analysis. Therefore, we present a complete method here. Other models will also be compared using the factors of our study to ensure the fairness of comparison.

(a) Performance of proposed multi-ANFISs_GRA scheme

The GRG of seven input factors are shown in Fig. 3. From this figure, we can see that the influence level of wind speed and precipitation are lower than the other factors. Thus, the remaining five major conditions are considered for the prediction. In this section, we present the comparison results for different structures of membership functions. The performance and the number of membership functions of each input are listed in Table 4. The



(a) MFs for temperature

(b) MFs for sunshine duration

(c) MFs for solar radiation

(d) MFs for cloud covering

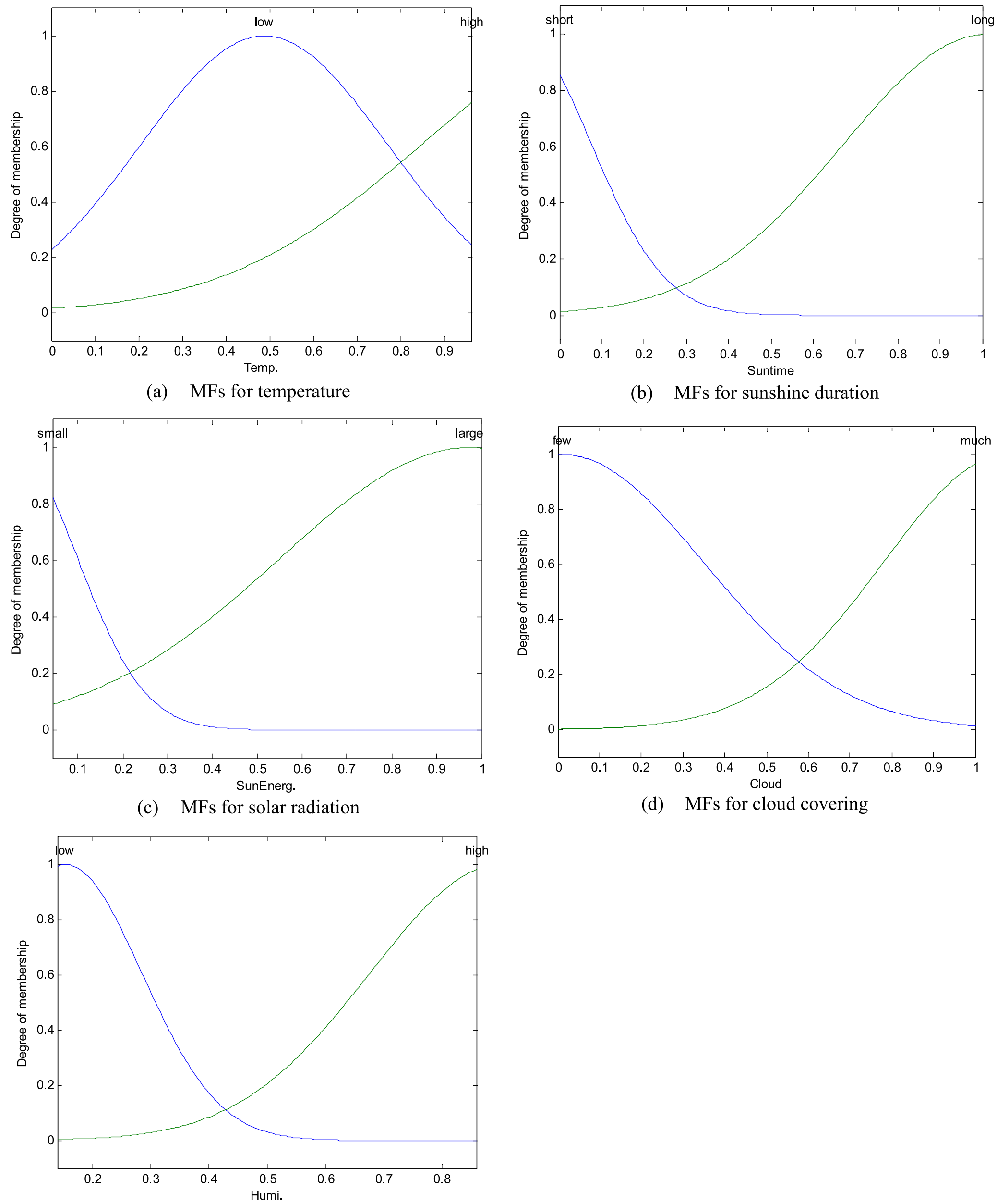
(e) MFs for relative humidity

Fig. 5. Membership functions for W1S1.

number on the table denotes the fuzzy partition, e.g., Structure 1 has five inputs and each input has two membership functions. All inputs, outputs, and targets are normalized. From Table 4, we observe that Structure 1 has a smaller testing MSE. Therefore, we choose Structure 1 as the final model. The prediction of the training dataset and the testing dataset using Structure 1 is shown in Fig. 4. Fig. 4(a) and (b) are the training and testing results, respectively. The corresponding membership functions (MFs) of each input of Structure 1 are shown in Figs. 5, 6, and 7. According to the results presented earlier, we can see that the proposed method can predict electricity consumption with MSE less than 3%.

(b) Discussion of using GRA

We introduce a comparison result of multi-ANFISs using seven and five parameters, i.e., discussion of GRA effectiveness. Table 5 lists the comparison results of ANFIS using five (multi-ANFISs_GRA) and seven conditions (multi-ANFISs). The corresponding membership functions of each input factor are listed in Table 5. As shown inTable 5, ANFIS with seven inputs has a high computational effort (approximately 15 min) due to more tuning parameters (1052) and fuzzy rules (192), while the multi-ANFISs_GRA has a lower computational time (1 min 24 s) in which the fuzzy rules of the single model are 32 and the tuning parameters are 212. The corresponding MSE of multi-ANFISs_GRA is approximately 8 times better than the results of multi-ANFISs. This illustrates the effectiveness of GRA.



(a) MFs for temperature

(b) MFs for sunshine duration

(c) MFs for solar radiation

(d) MFs for cloud covering

(e) MFs for relative humidity

Fig. 6. Membership functions for W1S0.

Table 5
Comparison and illustration of ANFISs using GRA.

	Number of membership functions							Epochs	Testing MSE	Time
	Temp.	Wind Speed	Precip.	Sunshine Duration	Solar radiation	Cloud	Relative Humi.			
Multi-ANFISs	2	2	3	2	2	2	2	500 epoch	**0.2159**	**15 min**
Multi-ANFISs_GRA	2			2	2	2	2	each ANFIS	**0.0273**	**1 min 24 s**

Table 6
Comparison of single ANFIS and multi-ANFISs_GRA.

	Number of membership functions							Number of parameters	Testing MSE	Epochs	Time
	Temp.	Sunshine Duration	Solar radiation	Cloud	Relative Humi.	Working day	School day				
Single ANFIS	2	2	2	2	2	2	2	**1052**	**0.0111**	**500**	**4 min**
Multi-ANFISs_GRA	2	2	2	2	2			**212 × 3**	**0.0273**	**500 each model**	**1 min 24 s**

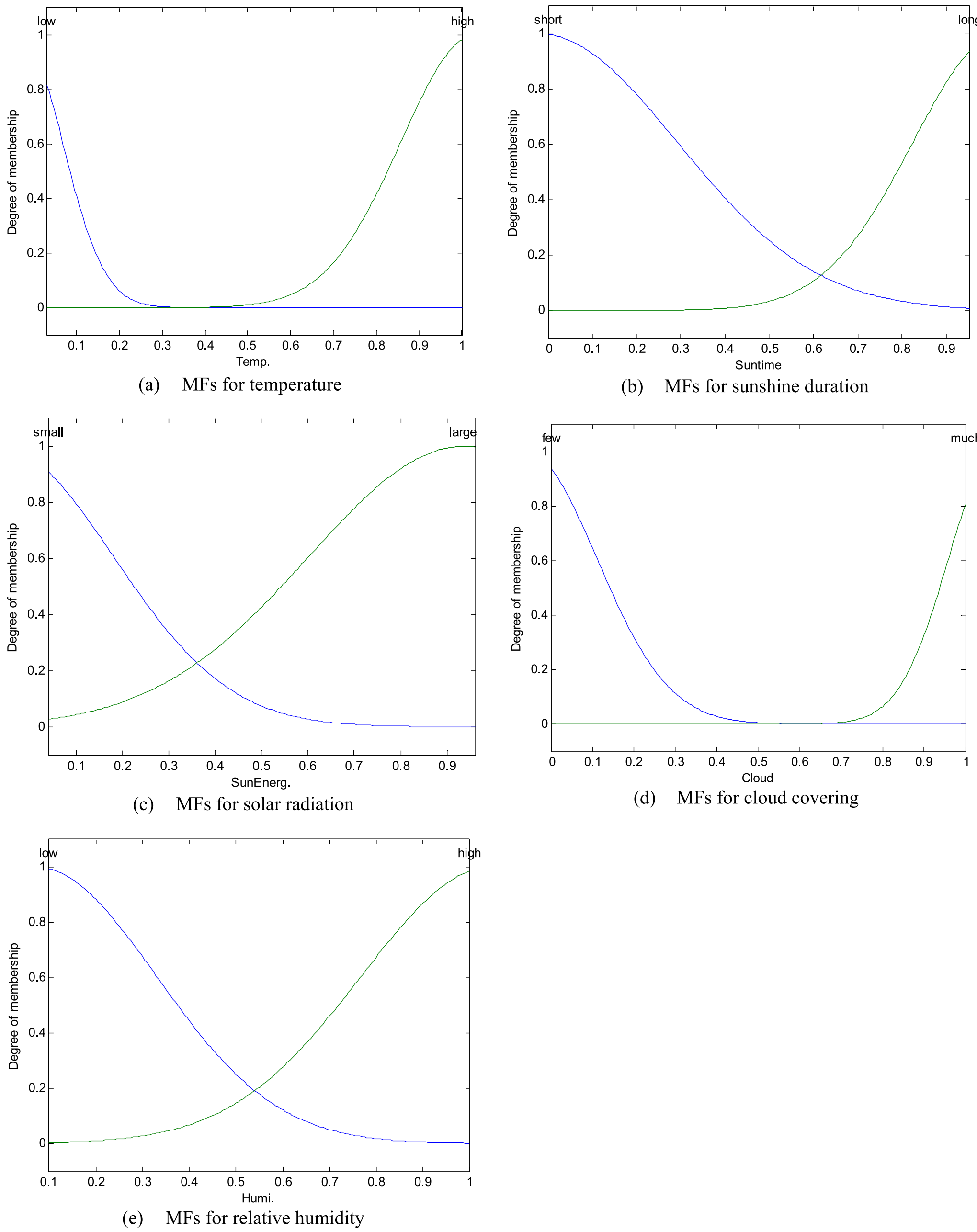


Fig. 7. Membership functions for W0S0.

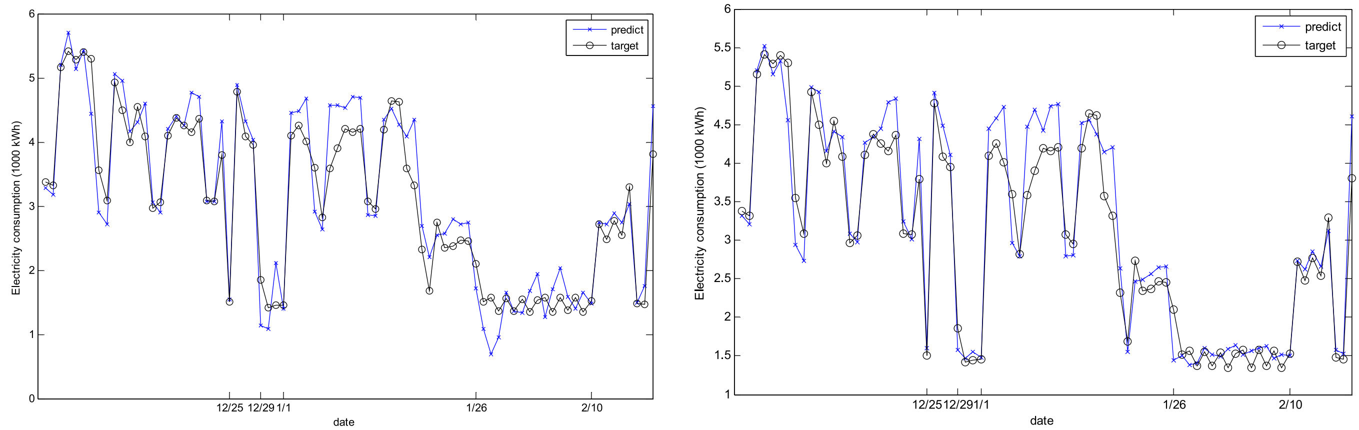
In the following discussions, the multi-ANFISs_GRA is adopted for demonstrations.

(c) Discussion of ANFIS models

Here, we discuss the effectiveness of using ANFIS models. Comparison results of prediction performance using ANFISs with the same weather conditions input factors and adding working day and school day conditions as inputs are introduced, denoted as multi-ANFISs_GRA and single ANFIS. Table 6 lists the corresponding structure, learning parameters, predicted MSE, and computational effort (time). We can find that these two systems have a similar performance in MSE, while the single ANFIS model performs better with a larger computational time (4 min). The corresponding predictions of models using the testing dataset are shown in Fig. 8, 8(a) and (b) are results of multi-ANFIS_GRA and single ANFIS, respectively (blue lines represent prediction, black lines indicate the actual data). From Fig. 8, we observe that there is a large prediction error during the New Year's holiday and winter vacation. Single ANFIS has better accuracy since it uses the whole dataset to train model. However, if we observe the membership function of the single ANFIS, we can notice the unreasonable membership function of using single ANFIS, as shown in Fig. 9. Also, the structure of multi-ANFISs_GRA is simpler than the single ANFIS model since the number of the parameters is only 60.5% of single ANFIS.

(d) Comparison on models (ANFIS and LM-BP)

In this discussion, we have the comparison results between LM-BPs and ANFISs. We use the same scheme as shown in Fig. 2 with the ANFISs are replaced by three LM-BP models, and the corresponding parameters are introduced in Table 7. Table 8 lists the corresponding comparison results of testing MSEs. The computational effort (time) of LM-BPs is larger than ANFISs and the results of LM-BPs have better MSEs than ANFISs, however, the ANFISs are acceptable with explainable models and less parameters compared to LM-BP. The corresponding fuzzy rules of ANFISs



(a) (b)

Fig. 8. Prediction results using multi-ANFISs_GRA and single ANFIS . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

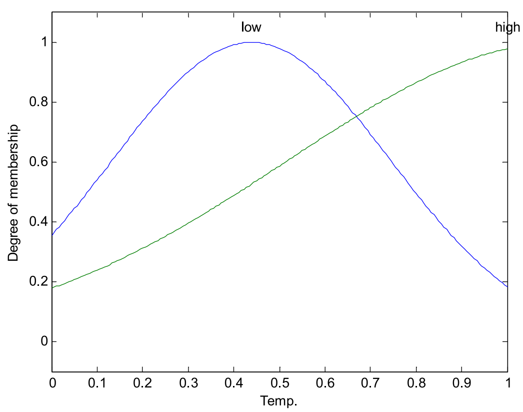


Fig. 9. MFs of temperature using single ANFIS.

after training are introduced in Appendix. The prediction results of two models are shown in Fig. 10, 10(a) and (b) are results of ANFIS and LM-BP (blue: prediction result, black: actual values)

(e) Comparison with other models

First, we compare the results of the proposed method, linear regression, and nonlinear regression. The comparison of MAPE is listed in Table 9. The corresponding predictions using regression models are shown in Fig. 11, 11(a) denotes the linear regression result, and Fig. 11(b) is the nonlinear regression. We can find that the result of our approach (multi-ANFISs_GRA) is better than the results of regression methods. However, the regression models are less complicated. Fig. 12 introduces the comparison of parameters using different models. The figure shows that our proposed method gets a better balance between model complexity and performance.

A comparison result with a deep learning approach (denotes PACF+SAE (Li et al., 2017), a combination of time series prediction and deep learning methods) is introduced to illustrate the effectiveness and performance of our approach. We briefly introduce it here. Partial auto-correlation function (PACF) is applied to analyze the correlation between recent and past data. The input variables of the time series can be evaluated according to the PACF values. Then, the sparse autoencoder (SAE) is used to build the predicted model. The number of lags is chosen as 30 since we consider that time affects electricity within a period of 30 days. The threshold of auto-correlation is chosen as ±0.2.

Table 7
Parameters of each LM-BP.

Parameters	Value
Max epoch	5000
Performance goal	0
Minimum of gradient	10^{-14}
Initial μ	0.05
Increase of μ	0.5
Decrease of μ	1000
Structure of hidden layer	13–17–13 with biases (number of parameters: 564)
Activation function	Hyperbolic tangent (tansig)
Learning rate	0.01

Table 8
Comparison of LM-BPs and ANFISs.

	Number of parameters	Testing MSE	Time
Multi-LM-BPs	564 × 3	0.013	4 min 43 s
Multi-ANFISs	212 × 3	0.0273	1 min 24 s

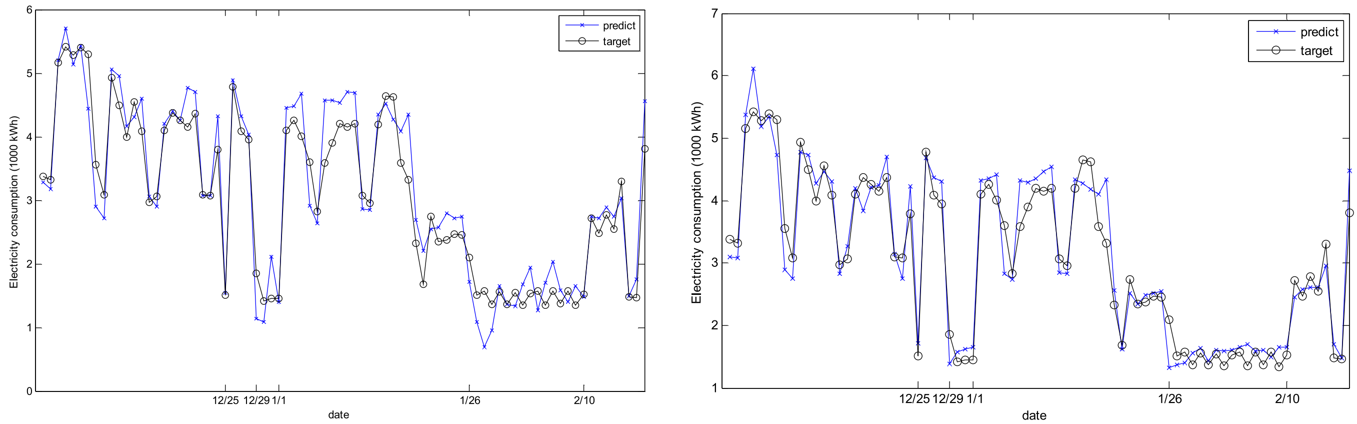
Table 9
Comparing MAPE of part (e).

Model	MAPE of testing data
Multi-ANFISs_GRA	12.25%
Linear regression	17.07%
Nonlinear regression	16.0%

The result of PACF is shown in Fig. 13. The determined optimal input variables with respect to electricity consumption $y(p)$ are $x_1 = y(p-14)$, $x_2 = y(p-8)$, $x_3 = y(p-7)$, $x_4 = y(p-6)$, and $x_5 = y(p-1)$. Subsequently, the autoencoder is trained and the inputs are the five variables chosen by PACF. The number of nodes of the single hidden layer inside the autoencoder is 100. L1 regularizer is applied with the value of 0.0002. The decoder is removed, and we get a two-layer back-propagation neural network (BPNN) for prediction. There are 32 nodes in the first hidden layer and 16 in the second layer. The result is shown in Fig. 14. The MAPE of PACF+SAE is 21.9%. Though we use a deep learning method, the performance is not comparable to our proposed method and other simple methods.

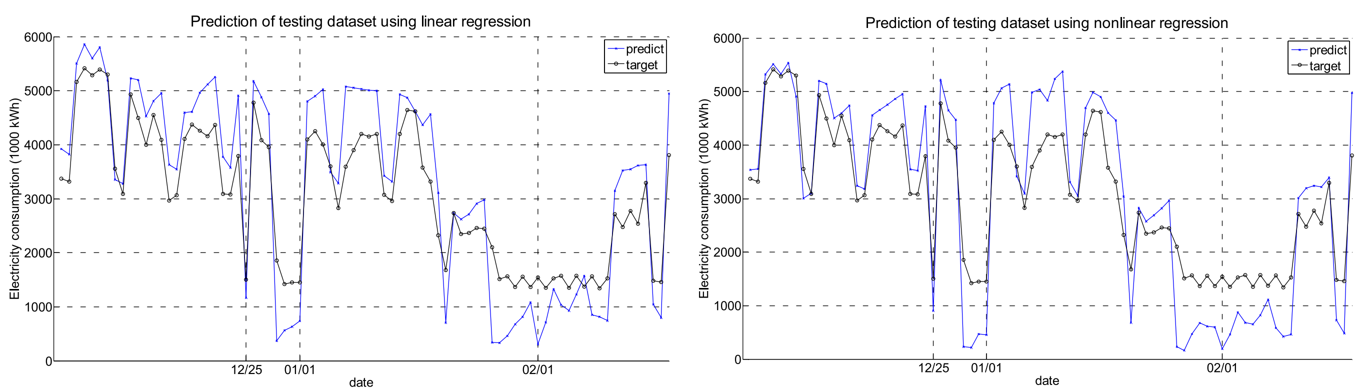
(f) *Alarm system of abnormal situation*

In this section, we discuss how to detect the unusual electricity consumption by the proposed multi-ANFISs_GRA. Comparing the



(a) (b)

Fig. 10. Prediction of multi-ANFISs and multi-LM-BPs.



(a) (b)

Fig. 11. Prediction results using regression models.

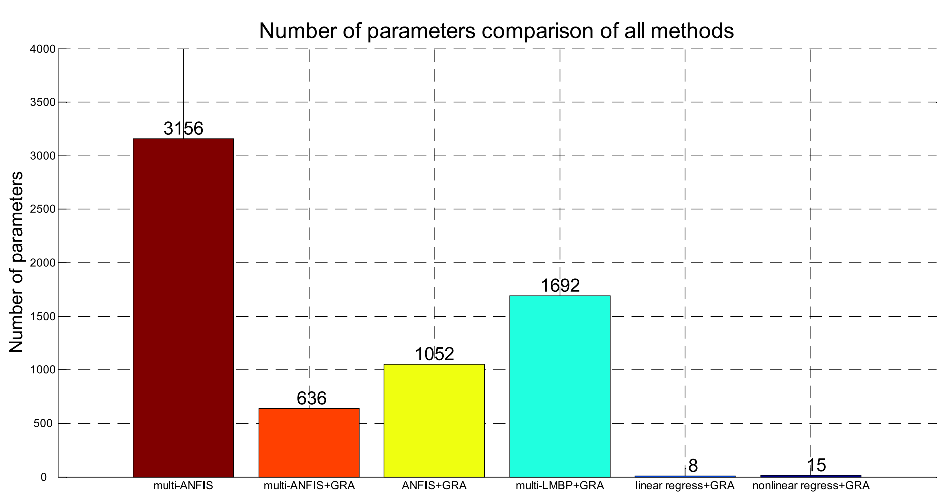


Fig. 12. Comparing number of parameters using different models.

prediction errors, we observe the results and find time periods with obvious errors owing to corresponding events from the calendar of Providence University and the website of the Library of Providence University. Finally, we have the following observations from the events and the corresponding predicted errors. The predicted performances are introduced in Fig. 15, (a) examination; (b) library activity for fresh student; and (c) last day of semester. The established alarm system is designed using the following observations:

1. ***Examination:*** We find that the electricity consumption a week before the examination has an evident error, as shown in Fig. 15(a). Fig. 15(a) shows the prediction results

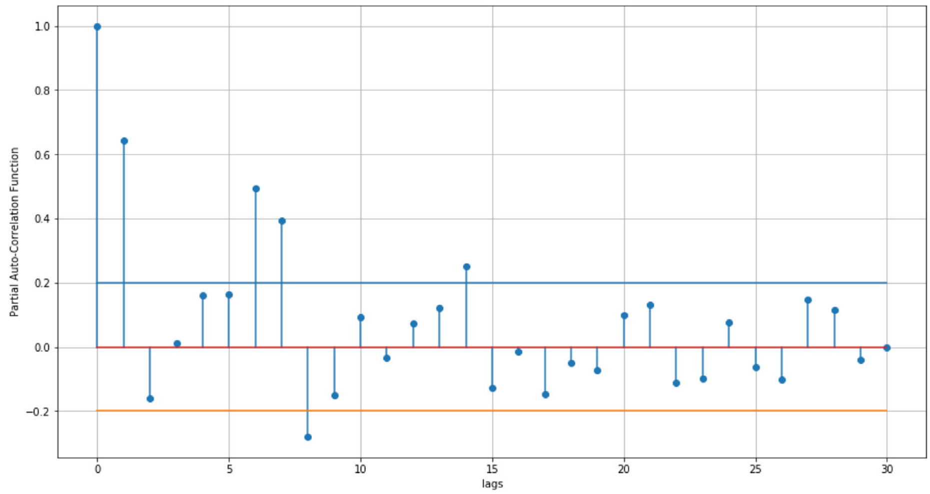


Fig. 13. Partial auto-correlation of electricity consumption with 30 lags.

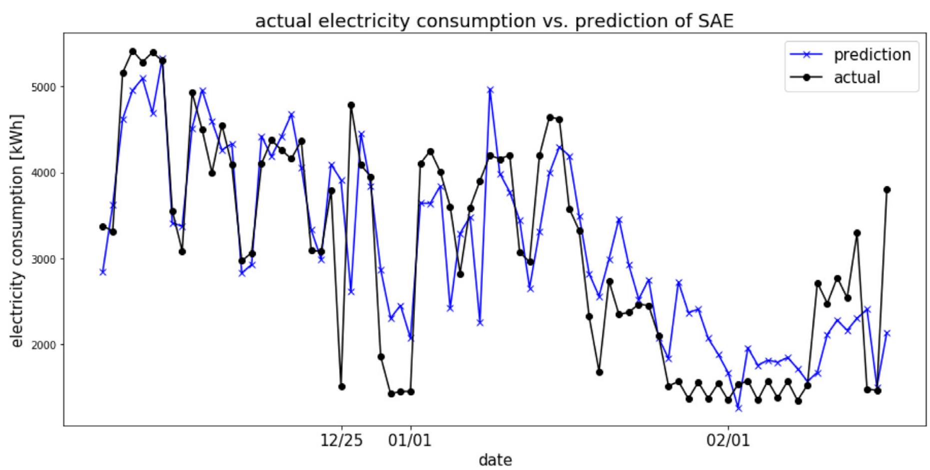


Fig. 14. Prediction result of SAE versus actual values.

during the examination period (June 19, 2017). The electricity consumption of June 12 to 16, 2017 is higher than the prediction. We compute all the prediction errors of corresponding events. The range of the differences comparing to prediction is between −25.8% and 23.8%.

2. ***Events held by library:*** Human activity is a main factor of electricity consumption. We can also see the corresponding phenomenon by observing the divergence between prediction and actual data. Fig. 15(b) shows that the electricity consumption of this week is much higher than the prediction. According to the website of the library, it held a welcome event for freshmen from October 16 to 20, 2017. In the other words, there were more people than usual. We also compare the difference between the same period of 2017 and 2018 (Fig. 15(c)). The consumption of 2017 is higher than the data of 2018 by approximately 15%. The maximum difference compared to the model is 25.4%.
3. ***The last day of the semester:*** Though the school arranges the exam week, most departments only need a couple of days instead of the entire week. This circumstance can be observed at the final exam week since the students who get accommodations may go home right after they finish the tests. From Fig. 15(d), at January 9, 2017, it is the first day of the final exam week. We can notice that the electricity consumption is lower than the prediction from the fourth day of the exam week. The same situation can be observed in 2018. The differences between the actual data compared to the prediction is between −1.9% to −75.3%. The average is −27.71%.

According to these cases, we set up an alarm threshold which can inform the users and exclude most of these situations. The value we choose is ±40% with a safety factor 1.5. If the difference is out of this range, the system will show an alarm so that the person in charge can handle it as soon as possible. In Fig. 16, we use data from December 2018 to February 18, 2019 to show a simple alarm application. The black line is the prediction of the proposed model. The yellow region is the acceptable region, which means the error is within ±40% of prediction. The red points and the blue points are actual data points. The blue points are inside the acceptable region. The red points are outside the region, which represents that the error between actual data and output of the alarm system is greater than 40%.

6. Conclusions

In this study, we have proposed a predictive and explainable forecast method based on ANFIS with multiple models. GRA evaluates and selects the input factors. By inputting the selected environment factors, e.g., temperature, sunshine duration, and

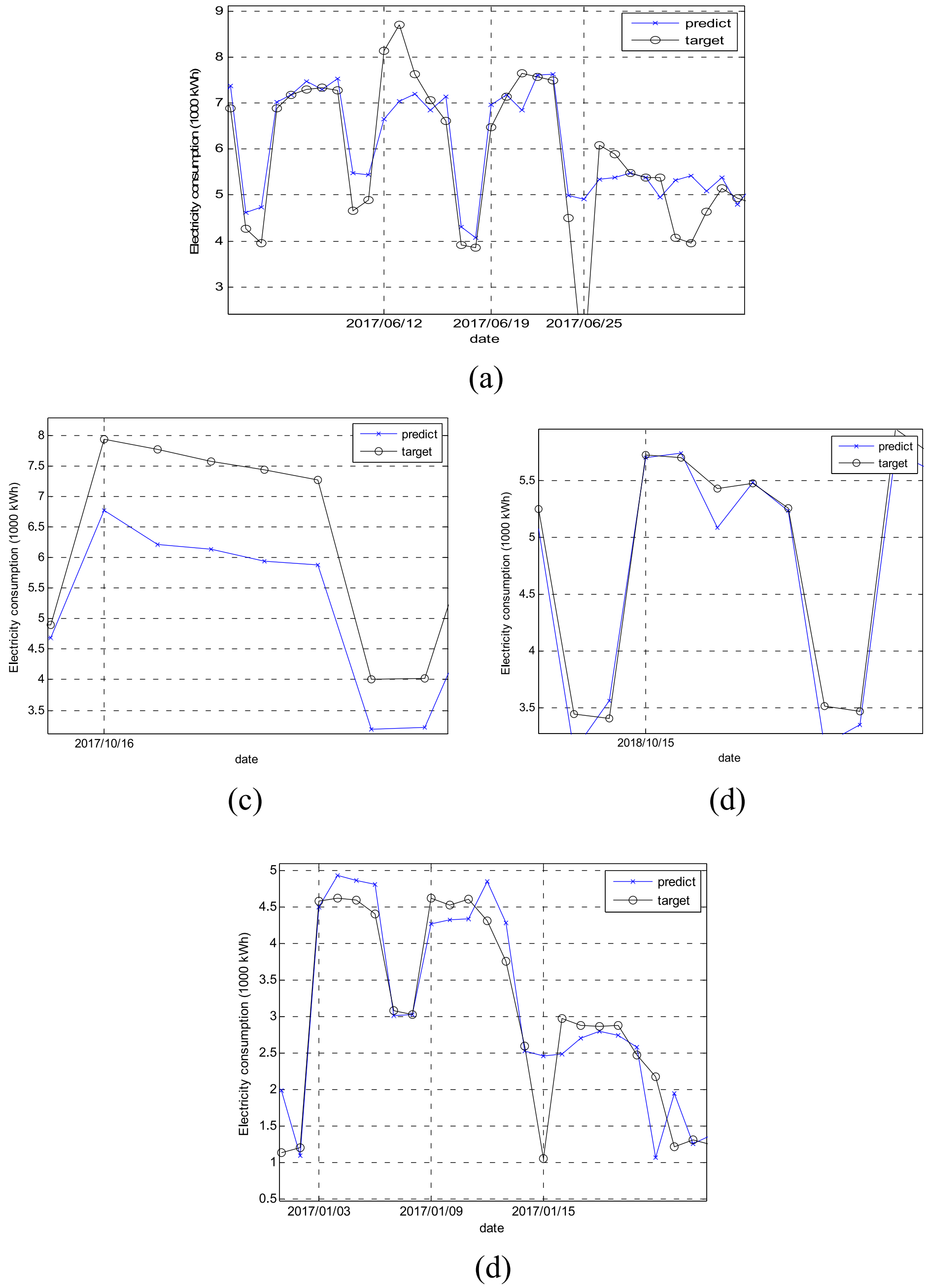


Fig. 15. Prediction results of human activity events.

solar radiation and the working day and school day conditions, the consumption of electricity of a school library can be predicted and analyzed. Multiple models are more flexible because the models of different categories are trained independently. We can adjust the models for different situations, for example, in the case of our study, we can add more data for the model of the holiday condition to improve the accuracy. ANFIS is a combination of fuzzy inference systems and a structure of neural networks. It can infer the relationship between inputs and output, which neural networks cannot show us. The integration of multiple models and ANFIS provide a faster method for forecasting electricity consumption by inputting effective factors. The factors are different in different buildings according to the function of each one. We used single ANFIS, LM-BPs, regressions, and SAE as comparisons. The results showed that multi-ANFISs is slightly less accurate than the single ANFIS and LM-BPs, which are complicated models. When comparing with simple models like regression methods, multi-ANFISs show a much better performance. We conclude that multi-ANFISs_GRA can be used not only for predicting the electricity consumption, but also for specific correlation between factors and the use of electricity. At the same time, multi-ANFISs_GRA has a simpler structure. We also provided an alarm threshold to determine unusual electricity consumption. The prediction can be a reference of the contract of electricity consumption mentioned in the Introduction. This application can reduce both electricity fee and the chance of emergency power supply. For the alarm application, since Taiwan is a country with a lot of typhoons in summer, we can try to analyze the influence of short-time power failure caused by bad weather and define a new threshold for abnormal electricity consumption.

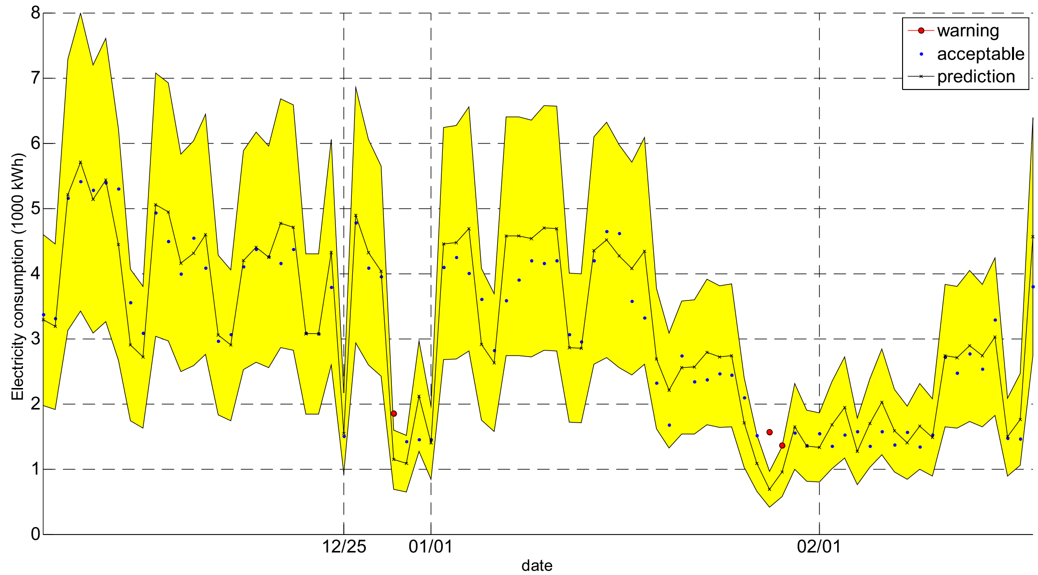


Fig. 16. Illustration of alarm criterion from prediction result . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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Appendix. FUzzy rules of ANFIS

In the following, $\mathbf{X}$ denotes the input variables [Temp., Suntime, SunEnerg., Cloud, Humi. 1]^T.

A.1. Fuzzy rules of ANFIS-surface of W1S1

1. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.001088 0.00113 0.001302 0.001802 0.001426 0.002904]$\times\mathbf{X}$)
2. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.0278 0.01195 0.01678 0.03051 0.02921 0.05287] $\times\mathbf{X}$)
3. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.005011 0.005049 0.008594 0.02243 0.01267 0.02677] $\times\mathbf{X}$)
4. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.155 0.02248 0.0639 0.07746 0.02423 0.1507] $\times\mathbf{X}$)
5. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.001429 0.003826 0.003181 0.003687 0.001986 0.006513] $\times\mathbf{X}$)
6. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.1294 0.1093 0.1071 0.1561 0.1363 0.3382] $\times\mathbf{X}$)
7. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [−0.003383 0.02979 0.03133 0.05931 0.02041 0.07757] $\times\mathbf{X}$)
8. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.02292 −0.01354 −0.03438 0.1237 −0.03887 0.2854] $\times\mathbf{X}$)
9. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.002701 0.003814 0.003297 0.001227 0.002001 0.005223] $\times\mathbf{X}$)
10. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.008989 0.007594 0.008134 0.01038 0.009694 0.01919] $\times\mathbf{X}$)
11. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.001709 0.002734 0.003368 0.005865 0.003155 0.007938] $\times\mathbf{X}$)
12. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.01335 0.01268 0.0142 0.02344 0.01724 0.03648] $\times\mathbf{X}$)
13. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.09742 0.2004 0.0466 −0.04086 −0.0004338 0.1694] $\times\mathbf{X}$)
14. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.05012 0.1601 0.0627 −0.0405 −0.1061 0.2356] $\times\mathbf{X}$)
15. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.01604 0.04283 0.04486 0.06892 0.02987 0.1014] $\times\mathbf{X}$)
16. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [−0.1535 0.08494 −0.08169 0.1788 −0.03485 0.3537] $\times\mathbf{X}$)
17. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.004695 0.002844 0.003539 0.003391 0.003616 0.006264] $\times\mathbf{X}$)

18. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.05371 0.02144 0.03081 0.04329 0.05078 0.07616] $\times\mathbf{X}$)
19. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.01747 0.004209 0.009524 0.0202 0.01479 0.02422] $\times\mathbf{X}$)
20. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.2786 0.04487 0.09327 0.2883 0.2486 0.3567] $\times\mathbf{X}$)
21. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.01397 0.01194 0.0121 0.006632 0.008684 0.01733] $\times\mathbf{X}$)
22. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.149 0.06217 0.05211 0.09296 0.1101 0.2061] $\times\mathbf{X}$)
23. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.01038 0.009281 0.009253 0.01101 0.008396 0.01805] $\times\mathbf{X}$)
24. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.3208 0.09191 0.1233 0.1132 0.2451 0.2256] $\times\mathbf{X}$)
25. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.0103 0.01108 0.01027 0.003353 0.006273 0.0147] $\times\mathbf{X}$)
26. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.03492 0.025 0.02782 0.0207 0.02842 0.04653] $\times\mathbf{X}$)
27. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.006833 0.004558 0.005627 0.005483 0.005208 0.009211] $\times\mathbf{X}$)
28. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.06103 0.02724 0.03518 0.04882 0.04775 0.07389] $\times\mathbf{X}$)
29. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.08639 0.1437 0.04352 −0.004991 0.01717 0.1568] $\times\mathbf{X}$)
30. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.5576 0.2208 −0.3355 0.1089 −0.004861 0.4917] $\times\mathbf{X}$)
31. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.04189 0.03048 0.03179 0.02144 0.02536 0.05497] $\times\mathbf{X}$)
32. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.5123 −0.04301 −0.2238 0.1485 0.2356 0.3214] $\times\mathbf{X}$)

A.2. Fuzzy rules of ANFIS-surface of W1S0

1. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.001086 0.001129 0.0013 0.001799 0.001424 0.0029] $\times\mathbf{X}$)
2. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.01238 0.006291 0.007785 0.01085 0.01482 0.0213] $\times\mathbf{X}$)
3. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.004984 0.005048 0.008578 0.02235 0.01263 0.02669] $\times\mathbf{X}$)
4. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.04418 0.02973 0.05642 0.04596 0.03936 0.06883] $\times\mathbf{X}$)
5. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.001372 0.003885 0.003172 0.003569 0.001951 0.006496] $\times\mathbf{X}$)
6. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.09828 0.04516 0.05483 0.06087 0.1133 0.1535] $\times\mathbf{X}$)
7. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [−0.003524 0.02971 0.03119 0.05908 0.02028 0.07728] $\times\mathbf{X}$)
8. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [−0.09197 0.02387 −0.04338 0.04695 0.07725 0.08976] $\times\mathbf{X}$)
9. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.002682 0.003839 0.003307 0.001184 0.001987 0.005218] $\times\mathbf{X}$)
10. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.008099 0.008851 0.00784 0.005801 0.0104 0.0161] $\times\mathbf{X}$)
11. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.001703 0.002726 0.003361 0.005854 0.003149 0.007918] $\times\mathbf{X}$)
12. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.01071 0.009119 0.01127 0.02062 0.01746 0.02853] $\times\mathbf{X}$)
13. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.06332 0.1624 −0.0004843 −0.04582 −0.0068 0.127] $\times\mathbf{X}$)
14. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [−0.03652 0.05365 −0.07189 0.02001 0.01848 0.1905] $\times\mathbf{X}$)
15. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.01448 0.04128 0.04279 0.06738 0.02902 0.09854] $\times\mathbf{X}$)
16. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [−0.07287 −0.02195 −0.09935 0.04318 0.0882 0.1579] $\times\mathbf{X}$)
17. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.004695 0.002844 0.003539 0.00339 0.003615 0.006263] $\times\mathbf{X}$)
18. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.0472 0.01912 0.02674 0.03413 0.04357 0.06227] $\times\mathbf{X}$)
19. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.01746 0.004208 0.009522 0.02019 0.01478 0.0242] $\times\mathbf{X}$)
20. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.2539 0.04286 0.07685 0.2273 0.1897 0.2745] $\times\mathbf{X}$)
21. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.01394 0.01195 0.01209 0.006597 0.008672 0.01732] $\times\mathbf{X}$)
22. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.2452 0.1108 0.1411 0.1382 0.2 0.2891] $\times\mathbf{X}$)

23. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.01032 0.009253 0.009196 0.01092 0.008347 0.01794] $\times\mathbf{X}$)
24. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.3783 0.1071 0.09315 0.09859 0.2051 0.282] $\times\mathbf{X}$)
25. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.0103 0.01109 0.01027 0.003345 0.006272 0.0147] $\times\mathbf{X}$)
26. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.0343 0.02512 0.02747 0.01913 0.02846 0.04504] $\times\mathbf{X}$)
27. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.006832 0.004556 0.005625 0.00548 0.005206 0.009207] $\times\mathbf{X}$)
28. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.06013 0.02626 0.03429 0.04786 0.04797 0.07126] $\times\mathbf{X}$)
29. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.06722 0.1194 0.01695 −0.007282 0.0123 0.1289]$\times\mathbf{X}$)
30. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.4559 −0.03064 −0.131 0.2562 0.1823 0.3195] $\times\mathbf{X}$)
31. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.04061 0.02946 0.03041 0.02051 0.02479 0.05323] $\times\mathbf{X}$)
32. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.4267 −0.0752 −0.1407 −0.01246 0.1913 0.292] $\times\mathbf{X}$)

A.3. Fuzzy rules of ANFIS-surface of W0S0

1. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.001407 −0.01757 −0.01459 −0.005075 −0.004438 −0.02122] $\times\mathbf{X}$)
2. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.01389 0.001003 −0.002786 0.002199 −0.001701 0.003698] $\times\mathbf{X}$)
3. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.0962 0.008526 0.02826 0.01269 0.0006347 0.02919] $\times\mathbf{X}$)
4. If (Temp. is low) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.1556 0.01833 0.01493 0.004455 −0.05347 0.002206] $\times\mathbf{X}$)
5. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [−0.006357 −0.01512 −0.01555 −0.01798 −0.01343 −0.02805] $\times\mathbf{X}$)
6. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.01092 0.005484 0.004852 −0.009877 0.00556 0.004598] $\times\mathbf{X}$)
7. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.0232 −0.01624 −0.002639 0.01881 0.007631 0.009785] $\times\mathbf{X}$)
8. If (Temp. is low) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.02599 −0.01623 0.002511 0.02681 −0.005619 0.0183] $\times\mathbf{X}$)
9. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [−0.007639 0.1049 0.05058 −0.02346 −0.003216 0.09709] $\times\mathbf{X}$)
10. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.003183 −0.02651 −0.01903 −0.01159 −0.009184 −0.02802] $\times\mathbf{X}$)
11. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.001334 −0.01127 −0.01054 −0.008705 −0.006271 −0.01983] $\times\mathbf{X}$)
12. If (Temp. is low) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.0171 0.001306 −0.0006532 0.0006805 0.001949 0.003433] $\times\mathbf{X}$)
13. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [−0.03373 0.1017 0.03644 −0.05938 −0.05294 0.0927] $\times\mathbf{X}$)
14. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.009764 −0.04507 −0.01846 −0.0535 0.005171 −0.03752] $\times\mathbf{X}$)
15. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [0.0001028 −0.01105 −0.01003 −0.0111 −0.008933 −0.02334] $\times\mathbf{X}$)
16. If (Temp. is low) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.02335 0.006356 0.01151 0.008024 0.01385 0.01158] $\times\mathbf{X}$)
17. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.03878 0.02047 0.02309 0.04988 0.04293 0.0783] $\times\mathbf{X}$)
18. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.03407 0.001638 −0.02742 −0.01271 −0.1021 −0.06166] $\times\mathbf{X}$)
19. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [−0.1372 0.04845 0.08225 0.001602 0.07061 0.0934] $\times\mathbf{X}$)
20. If (Temp. is high) and (Suntime is short) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [−0.2942 −0.1587 −0.1923 0.3549 −0.262 0.2158] $\times\mathbf{X}$)
21. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [−0.0416 −0.001359 −0.03243 −0.02324 −0.02294 −0.03265] $\times\mathbf{X}$)
22. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.07955 0.1095 0.078 0.0953 0.01316 0.02077] $\times\mathbf{X}$)
23. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [−0.06498 0.01311 −0.001138 0.04555 0.02197 0.07213] $\times\mathbf{X}$)
24. If (Temp. is high) and (Suntime is short) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [0.1225 −0.2187 −0.05128 0.07252 −0.06178 0.07808] $\times\mathbf{X}$)
25. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is low) then (output is [0.02271 −0.01244 −0.007807 0.004681 −0.007978 −0.01197] $\times\mathbf{X}$)

26. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is few) and (Humi. is high) then (output is [0.119 0.07708 0.06623 0.06073 0.106 0.1431] $\times\mathbf{X}$)
27. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is low) then (output is [0.000322 0.003675 0.004733 0.007909 0.007348 0.009736] $\times\mathbf{X}$)
28. If (Temp. is high) and (Suntime is long) and (SunEnerg. is small) and (Cloud is much) and (Humi. is high) then (output is [0.001086 0.04777 0.03466 −0.002351 0.03077 0.04901] $\times\mathbf{X}$)
29. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is low) then (output is [0.1035 −0.02181 0.03819 −0.007867 −0.02285 0.02059] $\times\mathbf{X}$)
30. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is few) and (Humi. is high) then (output is [0.08737 −0.1835 0.008111 0.08812 0.07189 0.09713] $\times\mathbf{X}$)
31. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is low) then (output is [−0.001709 0.005811 0.01107 0.01174 −0.0001003 0.02528] $\times\mathbf{X}$)
32. If (Temp. is high) and (Suntime is long) and (SunEnerg. is large) and (Cloud is much) and (Humi. is high) then (output is [−0.08746 0.05875 0.03154 −0.004031 0.1148 0.1062] $\times\mathbf{X}$)

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