

# SAGA-FCM-LSSVM model-based short-term power forecasting of photovoltaic power plants

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**Abstract.** With the rapid development of social economy, vigorously developing solar energy has become a powerful means to solve energy and environmental problems. However, the instability of weather condition makes the output of PV power have strong randomness, fluctuations and intermittence. Thus accurate photovoltaic (PV) power forecast eliminates the negative impacts of the grid connection of PV power generation systems, which are very meaningful for effectively integrating the PV power systems into the grid. The paper presents a Simulate Anneal and Genetic Algorithm (SAGA), fuzzy c-means clustering (FCM) and least square support vector machine (LSSVM) (SAGA-FCM-LSSVM) model-based power short-term forecasting of PV power plants approach. The experimental effect of the proposed prediction method is verified by employing large datasets from the Desert Knowledge Australia Solar Center (DKASC) website. In this work, the FCM clustering algorithm is adopted to cluster the historical power datasets, and the LSSVM technique maps the multivariate meteorological factors and power data nonlinear relationship. The SAGA method is applied to improve the initial clustering centers of the FCM clustering algorithm to obtain a higher prediction performance. The prediction result of the method in this paper is contrasted with back propagation neural network (BPNN) and LSSVM models, and reveals excellent effect in improving the accuracy of prediction.

## 1. Introduction

In recent years, the photovoltaic (PV) market has witnessed a tremendous growth due to the significant cost reduction of the PV modules on the market and the proposed supporting policies [1]. However, the integration of solar energy into an electrical network hampers the grid management due to the randomness, fluctuations and intermittence of weather condition [2]. Therefore, accurately forecast the PV power generation in advance is of great significance to the efficient utilization of PV energy and the grid management [3].

Up to now, a variety of PV power generation prediction methods have been applied, which are categorized as physical methods and statistical methods according to the forecasting models [4]. The physical methods are based on solar radiation, air temperature, cloud amount and other weather factors to predict PV generation [5]. However, the uncertainty of meteorological factors challenges to the accurate prediction of PV power [6]. Considering the changeable weather effectively based on historical power datasets, the statistical methods are widely accepted [7]. Khan *et al* develops a back



propagation neural network (BPNN) model based on temperature, wind speed, humidity, solar radiation and air quality index to predict PV power production in haze weather [8]. Aziz et al. proposes a cuckoo search (CS)-least square support vector machine (LSSVM)-based approach for short-term power prediction with solar irradiation and ambient temperature as input attributes [9]. The method based on BPNN has a good approximation ability, but its convergence is slow and is likely to get into a local minimum extremely [10]. Furthermore, the prediction accuracy of LS-SVM approach is not high enough.

Owing to the shortcomings of BPNN and LS-SVM methods, the paper employs a SAGA-FCM-LSSVM model-based approach, which is valuable for the PV generation prediction with fast and exact forecasting performance. In particular, the proposed forecasting model can also be combined with the reconfiguration algorithm to determine the optimal array configuration under arbitrary operating conditions throughout the lifetime of the PV array, thus reducing the power derating caused by thermal related aging effects, which can optimize the life performances of the PV components [11,12].

## 2. Proposed architecture for the proposed PV power forecasting model

### 2.1. Proposed SAGA-FCM-LSSVM algorithm

**2.1.1. SAGA-FCM algorithm.** The FCM algorithm is a popular clustering method, which adopts the concept of geometric approximation. Nevertheless, FCM method is essentially a kind of improved local search approach.

In this paper, GA and SA algorithms are combined to cluster analysis. It overcomes the premature phenomenon of traditional GA because SA and GA can complement each other. Meanwhile, the genetic coding method and fitness function are designed according to the specific situation of the clustering problem, which makes the algorithm more effective and converges to the global optimal solution more quickly.

And the four statistical indicators of the PV output power which are *standard deviation*  $\sigma$ , *coefficient of variation*  $cv$ , *skewness*  $Sk$  and *kurtosis*  $kur$  after normalization are used as the eigenvalues of the cluster.

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - \bar{P})^2} \quad (1)$$

$$cv = \frac{\sigma}{\bar{P}} \quad (2)$$

$$Sk = \frac{N \cdot \sum_{i=1}^N (P_i - \bar{P})^3}{(N-1)(N-2) \cdot \sigma} \quad (3)$$

$$kur = \frac{\sum_{i=1}^N (P_i - \bar{P})^4}{(N-1) \cdot \sigma} \quad (4)$$

where  $P_i$  is the output power of a PV station at the time point.  $\bar{P}$  is the output power average.  $N$  represents the number of sample points a day.

**2.1.2. LS-SVM algorithm.** LS-SVM is an improved algorithm for SVM, which is an effective

approach for solving nonlinear issue, for instance, classification and function estimation. The principle of LSSVM is summarized as follows:

Let an  $n$ -dimensional vector sample be  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ , the sample is mapped from space  $R^n$  to feature space  $\varphi(x_i)$  by a nonlinear mapping  $\varphi(\cdot)$ , and the optimal decision function is constructed in the space:

$$f(x) = w^T \varphi(x) + b \quad (5)$$

where  $w^T$  is the weight coefficient vector of feature space,  $b$  is the bias.

The optimization issue of LS-SVM can be transformed into dual space as follows due to the principle of structural risk minimization:

$$L(w, b, e, \alpha) = \frac{1}{2} w^T w + c \sum_{i=1}^l e_i^2 - \sum_{i=1}^l \alpha_i [w^T \varphi(x_i) + b + e_i - y_i] \quad (6)$$

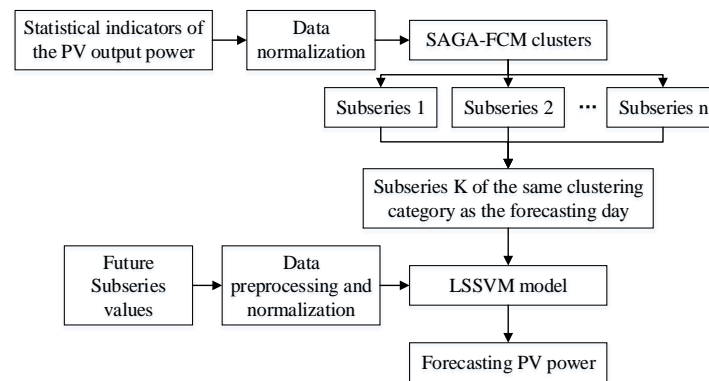
where  $\alpha_i$  is lagrange multiplier,  $c$  is regularization parameter.

The equation is simplified by using the optimization condition. According to Mercer, the inner product operation of  $\varphi(x_i)^T \varphi(x_j)$  can be replaced by the kernel function  $k(x_i, x_j)$ . Finally, the regression function of LS-SVM is obtained by solving it.

Table 1 indicates the input parameters for LS-SVM model. There are 8 parameters related to the actual multivariate meteorological factors and PV power datasets.

**Table 1.** Input variables of LS-SVM model.

Input	Variables
$x_1$	global horizontal radiation of 1 h before
$x_2$	air temperature of 1 h before
$x_3$	relative humidity of 1 h before
$x_4$	PV power of 1 h before
$x_5$	global horizontal radiation of 2 h before
$x_6$	air temperature of 2 h before
$x_7$	relative humidity of 2 h before
$x_8$	PV power of 2 h before



**Figure 1.** Process of the proposed PV power forecasting.

## 2.2. Proposed SAGA-FCM-LSSVM process

Figure 1 displays the PV generation forecasting process based upon the proposed SAGA-FCM-LSSVM model. First, the normalized statistical indicators of the PV output power are chosen as the inputs for the FCM clustering algorithm to categorize the historical power datasets into

different subseries. The decomposed original datasets of these subsets are applied to train LS-SVM model. The future multivariate meteorological factors and power values are adopted to predict the future PV power employing LS-SVM. The SAGA method is applied to improve the initial clustering centers of the FCM clustering algorithm to improve performance. The proposed approach in the paper is evaluated by adopting evaluation metrics and by contrasting with other prediction methods.

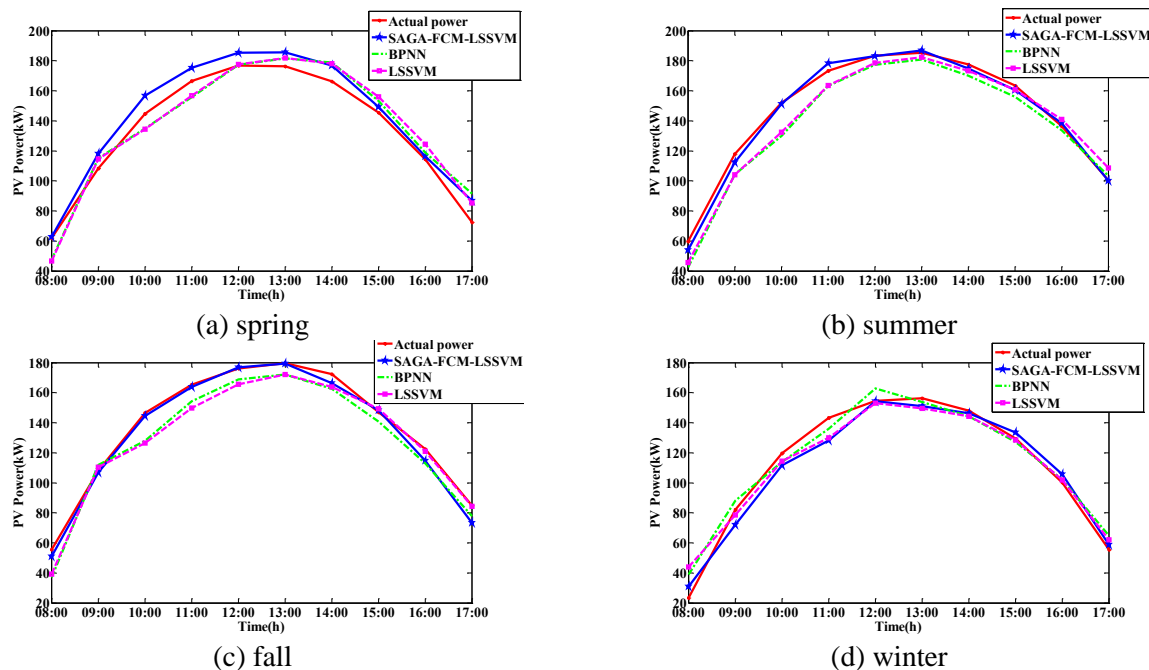
### 3. Experiments and result analysis

To verify the effect of the proposed prediction method based on SAGA-FCM-LSSVM model, BPNN method and LS-SVM method are applied in this paper. The multivariate meteorological factors (global horizontal radiation, air temperature and relative humidity) and historical power datasets from April 1, 2016 to March 30, 2018 are applied for the forecasting. The selected four forecasting days are September 14, 2017 (spring in Australia), February 26, 2018 (summer in Australia), March 30, 2018 (autumn in Australia) and July 29, 2017 (winter in Australia), which represent four seasons respectively.

The number of clustering categories and the Silhouette of the forecasting day are displayed in table 2. As can be obtained from the table 2, the Silhouette values of the selected four forecasting days are 0.4517, 0.4002, 0.3962 and 0.4428 when the number of clustering categories is 3.

**Table 2.** The number of clustering categories and the Silhouette of the forecasting day.

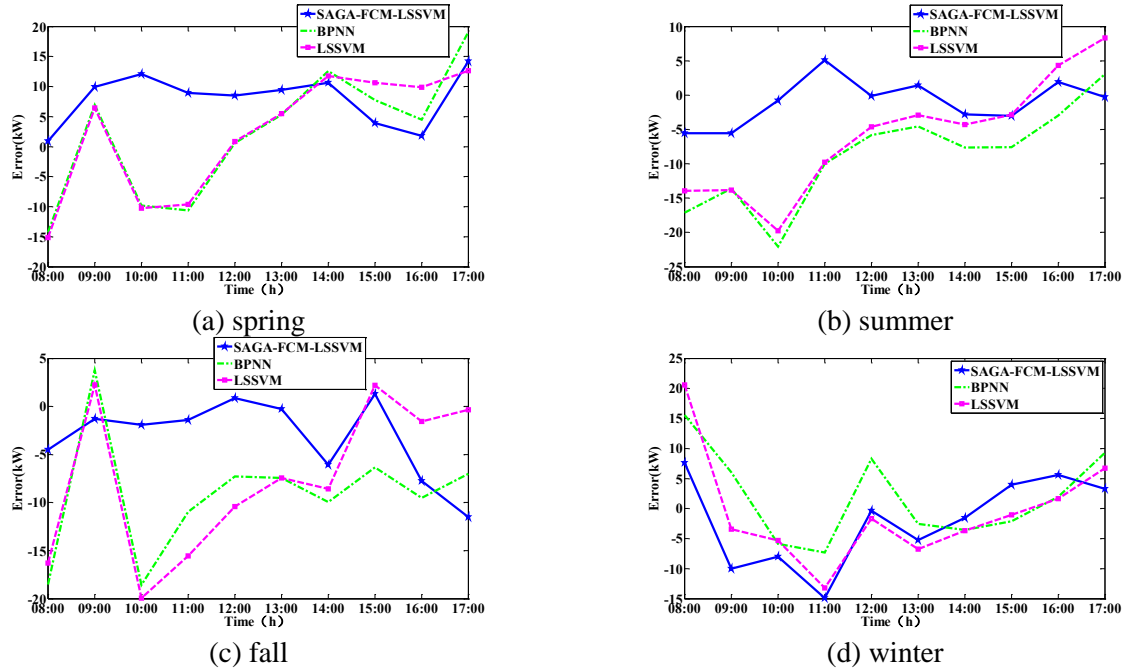
	Spring	Summer	Autumn	Winter
Categories	3	3	3	3
Silhouette	0.4517	0.4002	0.3962	0.4428



**Figure 2.** Prediction curves in different seasons.

The forecasting result curves by the SAGA-FCM-LSSVM forecasting model and the other forecasting models (BPNN and LS-SVM) are shown in figures 2(a)-2(d), respectively for spring, summer, fall and winter. From the results, it is clear that the SAGA-FCM-LSSVM model-based prediction method is more exact and reliable. Furthermore, figures 3(a)-3(d) show the corresponding

absolute errors curves on the selected four days. It can be obtained that the error of the SAGA-FCM-LSSVM model in each season is little and the prediction error distribution is limited in  $[-15, 15]$  kW.



**Figure 3.** Absolute error curves in different seasons.

The root mean square error (RMSE) [13], the mean absolute percentage error (MAPE) and the coefficient of determination ( $R^2$ ) metrics, shown in equations (7)–(10), are chose to evaluate the prediction performance.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_{f,i} - P_{m,i})^2} \quad (7)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left( \left| \frac{P_{f,i} - P_{m,i}}{P_{m,i}} \right| \right) \times 100 \quad (8)$$

$$\overline{P_{m,i}} = \frac{1}{N} \sum_{i=1}^N P_{m,i} \quad (9)$$

$$R^2 = \frac{(N \sum_{i=1}^N P_{f,i} P_{m,i} - \sum_{i=1}^N P_{f,i} \sum_{i=1}^N P_{m,i})^2}{(N \sum_{i=1}^N P_{f,i}^2 - (\sum_{i=1}^N P_{f,i})^2)(N \sum_{i=1}^N P_{m,i}^2 - (\sum_{i=1}^N P_{m,i})^2)} \quad (10)$$

where  $P_{f,i}$  is the  $i$ th prediction value of the power,  $P_{m,i}$  is the  $i$ th actual value of the power,  $N$  is the sample point numbers in the PV power generation period.

Table 3 indicates the prediction accuracy evaluation by adopting the RMSE, MAPE and  $R^2$ , considering the proposed SAGA-FCM-LSSVM model-based prediction technology and the other

comparative prediction approaches (BPNN and LS-SVM). It can be concluded that the proposed model results in better prediction accuracy: the RMSE, MAPE and  $R^2$  have 6.1970 kW, 4.006% and 0.9890 average values. The average RMSE enhancement of the proposed model with respect to the previous comparative models is 41.37% and 37.29%. And the average MAPE enhancement is 40.85% and 35.36%, respectively.

Therefore, compared with BPNN and LS-SVM approaches, the average amplitudes of prediction error of the proposed method are smaller. Synthetically, the proposed SAGA-FCM-LSSVM model is a novel and effective short-term PV power generation prediction model.

**Table 3.** Comparison of the prediction error by adopting various prediction methods.

	BPNN	LS-SVM	SAGA-FCM-LSSVM
RMSE (kW) Spring	11.0058	10.0473	9.0523
Summer	11.7520	10.0885	3.3372
Fall	11.1385	10.7465	5.0945
Winter	8.3804	8.6486	7.4041
Average	10.5692	9.8827	<b>6.1970</b>
MAPE (%) Spring	7.1923	6.9588	6.0262
Summer	6.6781	5.8421	1.8333
Fall	7.3188	6.2311	2.7140
Winter	5.9008	5.7562	5.4505
Average	6.7725	6.1971	<b>4.006</b>
$R^2$ Spring	0.9341	0.9459	0.9903
Summer	0.9665	0.9602	0.9957
Fall	0.9770	0.9637	0.9938
Winter	0.9779	0.9828	0.9761
Average	0.9639	0.9632	<b>0.9890</b>

#### 4. Conclusions

In the study, a new SAGA-FCM-LSSVM model-based method is proposed for short-term PV power generation forecasting. The original hourly global horizontal radiation, air temperature, relative humidity and PV power are taken as the inputs of the prediction model. Owing to the utilization of historical hourly multivariate meteorological factors and power, the input variables become more accurate, which is of great significance to the real-time prediction of PV power. Furthermore, the FCM clustering algorithm is applied to cluster the historical power datasets, the LS-SVM technique is adopted to train the forecasting model. The SAGA method is used to optimize the initial clustering centers of the FCM clustering algorithm. The datasets on the DKASC website are employed to verify the proposed method, by contrasting with BPNN and LS-SVM methods. The experimental results show that the smaller prediction error can be obtained by applying the proposed model, and its prediction performance is superior to the comparative models.

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The performance of the proposed forecasting approach was tested by using a large database from the Desert Knowledge Australia Solar Center (DKASC) website.

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