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Clustered Hybrid Wind Power Prediction Model Based on ARMA, PSO-SVM, and Clustering Methods

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ABSTRACT Wind power prediction is the key technology to the safe dispatch and stable operation of power system with large-scale integration of wind power. In this work, based on the historical data of wind power, wind speed and temperature, the autoregressive moving average (ARMA) prediction model and the support vector machine (SVM) prediction model are established, particle swarm optimization (PSO) algorithm is involved for parameter optimization of SVM model. Furthermore, a hybrid PSO-SVM-ARMA prediction model based on ARMA and PSO-SVM model is illustrated for wind power prediction, and the covariance minimization method and PSO are employed to find the optimal weights. Moreover, with the basis of clustering theory, time series are clustered to examine the effective dataset for wind power prediction, and a clustered hybrid PSO-SVM-ARMA (C-PSO-SVM-ARMA) wind power prediction model is prospectively proposed. In case study, different prediction models are carried out and the prediction performance is examined based on different evaluation indices, the C-PSO-SVM-ARMA model shows better performance for wind power prediction with computational efficiency and satisfying precision.

INDEX TERMS Autoregressive moving average (ARMA) model, clustered hybrid wind power prediction model, clustering method, particle swarm optimization (PSO), support vector machine (SVM).

I. INTRODUCTION

Wind power is facing a rapid development in recent 10 years. The latest GWEC report shows that the new installation of wind power of onshore and offshore is expected to be more than 55 GW each year until 2023 [1]. Power system is evolving into a grid with high penetration of renewable energy. Taking into account the stochastic characteristics of wind power, power system needs to meet the safe dispatch and stable operation of power grid while ensuring wind power consumption as much as possible.

To solve these problems, one solution is to increase the reserve capacity of classical generators. The volatility of wind power resource can be balanced or reduced by the switch on and off of traditional reserve capacity [2]–[4]. Another effective way is to improve the precision of wind power prediction. Power dispatch can be effectively carried out by a reliable reference of wind power prediction. With the comparison of the two available strategies, the investment and maintenance cost of equipment in the first solution is obviously huge. For the second solution, as far as the power prediction is accurate, power system can operate on a stable and low-cost status. As a result, wind power prediction technology is recognized as a key basic technology to improve the stable operation level of power systems with large-scale integration of wind power at present [5]–[7].

Time series analysis is widely used in data analysis research in economic, medical, meteorological, transportation and other industries, and it contains two main functions. The first function is prediction, it can predict the future data based on the historical data; another function is description, it can describe the changing law of the research object by establishing different models. Classical time series prediction methods include continuous method, moving average

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method, autoregressive moving average (ARMA) method, and GARCH (generalized auto-regressive conditional heteroskedasticity) method [8]–[11]. GARCH model can depict the higher order characteristics of time series, and it is first of all built on the foundation of an effective ARMA model. The order selection of ARMA is essential to the precision of prediction performance.

In recent years, heuristic technologies including support vector machine (SVM), artificial neural network (ANN), ant colony algorithm, and fuzzy logic algorithm are widely involved to wind power prediction [12]–[17]. Among these methods, SVM can provide prediction result based on limited set of information, it is useful when the parameters are optimized by other intelligent methods. Reference [15] introduced the support vector machine enhanced Markov model to derive better prediction performance of short-term wind power forecast.

Generally, a single comparatively good predictive model can be convictive, but may not be able to significantly decrease the prediction error. The combination theory is effective to improve the prediction performance of wind power by giving the optimal weights of different effective prediction models [18]–[20]. Reference [18] firstly introduced the combination method for model prediction. In [19], single grey models are united and a combination prediction model based on neural network is presented. A scoring approach is applied to combine plausible models to form an overall time-varying model in [20]. Based on the achievement of above reviewed research, it is good practice to improve wind power prediction by hybrid model such as to depict the intermittent and stochastic characteristic of wind power. Moreover, wind power shows different characteristics at different periods, to examine the effective dataset for short-term wind power prediction, it is also prospective to involve clustering theory to the prediction model and investigate on the reasonable segmentation strategy for wind power prediction.

In this paper, ARMA and SVM are employed and further prospectively combined and clustered to obtain a better hybrid wind power prediction model. The rest of paper is organized as follows: In Section II, the basic structure of ARMA and SVM models are introduced, particle swarm optimization (PSO) algorithm is involved for parameter optimization of SVM model and PSO-SVM model is narrated. Furthermore, the hybrid model named PSO-SVM-ARMA is illustrated with optimal weights. Then, in Section III, the clustering theory is introduced and a clustered hybrid PSO-SVM-ARMA (C-PSO-SVM-ARMA) model is proposed and the training strategy is highlighted. In the case study of Section IV, Based on the historical data of the east coast of the United States, the above models are established, prediction results are compared and analyzed based on four evaluation indices, and the prediction performance of C-PSO-SVM-ARMA model is verified. Finally, Section V concludes the findings.

II. THE HYBRID WIND POWER PREDICTION MODEL BASED ON ARMA AND SVM

A. THE ARMA MODEL

Auto-regressive moving average (ARMA) model can extract relevant information from the stationary time series, and can obtain helpful prediction results by using the limited historical data. For a stationary time series $\{x_t\}$, ARMA(p, q) model can be written as

$$x_t = \sum_{i=1}^{p} a_i x_{t-i} - \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

where, a_i is the autoregressive parameter, b_j is the moving average parameter, they are estimated by least square estimation in this work. ε_t is white Gaussian noise, p *is* the order of AR, and q is the order of MA. It can be found that ARMA(p, q) model treat the present prediction value as the linear combination of p historical values and q historical disturbances.

To make the ARMA model accurate, the candidate range for the orders (p, q) are first of all identified based on the characteristics of time series.

Generally speaking, ARMA model with higher order can obtain better prediction results, but it will take more computing resource. To weigh the role of both parts, based on the parameter estimation for each pair of (p, q), ordering criteria can be employed to help choose the best trade-off of the orders. AIC (Akaike information criterion) and BIC (Bayesian Information Criterion) are usually applied ordering criteria as shown in (2)-(3). The smallest AIC and BIC can pick out the model which possesses the satisfactory fitting accuracy and the optimal orders.

$$AIC(p, q) = \ln \sigma^2 + \frac{2(p+q+1)}{N} \tag{2}$$

$$BIC(p, q) = \ln \sigma^2 + \frac{\ln N(p+q+1)}{N} \tag{3}$$

where, σ is the error of the residual, N is the length of time series.

From the definition of AIC and BIC, each criterion contains two parts: the error of fitting part reflects the effect of model fitting after parameter estimation, smaller error indicate better model. The model complexity part reflect the complexity of ARMA, larger value indicates more occupation of computing resource.

In comparison of AIC and BIC, as the length of the time series increases, the model complexity of the BIC criterion tends to account for a higher proportion, so the orders of ARMA model selected by BIC criterion will be lower. In order to improve the accuracy of the prediction model, when the initial calculation of autocorrelation function and the partial autocorrelation function indicates small orders of ARMA, AIC criterion is more reasonable. In this work, AIC is employed.

In the modeling process of ARMA, the time series is usually required to be stationary. Based on the definition of (1), the ARMA model can be set up only when $\{\varepsilon_t\}$ follows Gauss distribution. As a result, the H_0 hypothesis test: $\{\varepsilon_t\}$ is white Gaussian noise should be carried out. In this wok, χ^2 test is used.

B. THE PSO-SVM MODEL

In order to take into account the influence factors such as wind speed, temperature and air pressure for wind power prediction, support vector machine (SVM) method is involved in this work. SVM was proposed by Vanpik in 1999 [21]. Integration of learning model and heuristic algorithm in this approach enable it to solve classification and regression analysis problems. Compared with the other traditional machine learning, SVM possesses stronger generalization performance [14].

The fundamental principle of SVM is, supposing there is a sample set $\{(\boldsymbol{x}_i, \boldsymbol{y}_i), i = 1, 2, \ldots, N\}$, each $\boldsymbol{x}_i \in R^n$ represents the input of sample space and has its mapping value $\boldsymbol{y}_i \in R$, N is relevant to the size of sample data. The basic idea is to map the input data vectors into a high-dimensional feature space, and then employ the following function to obtain the linear regression of feature space.

$$f(\boldsymbol{x}) = [\omega^T, \phi(\boldsymbol{x})] + b \tag{4}$$

where, $\phi(\boldsymbol{x})$ is the mapping function of a high-dimensional feature space, ω^T is the parameter estimated from the training dataset, and b is a constant coefficient. The linear regression of feature space obeys the following risk minimization rule as shown in (5) and the constraints of (6).

$$\min_{\omega,b,\xi_i,\xi_i^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=i}^{N}(\xi_i + \xi_i^*) \tag{5}$$

$$\begin{cases} \boldsymbol{y}_i - [\omega^T, & \phi(\boldsymbol{x}_i)] + b \le \varepsilon + \xi_i^* \\ [\omega^T, & \phi(\boldsymbol{x}_i)] + b - y_i \le \varepsilon + \xi_i \\ \xi_i, & \xi_i^* \ge 0 \end{cases} \tag{6}$$

where, $\boldsymbol{x}_i$ is the input vector, ξ_i, ξ_i^* are the relaxation factors that is related to loss coefficient ε, C is the penalty factor that is used to control regression quality.

In high-dimensional space, the inner product function $\phi(\boldsymbol{x}_i)$ can be replaced by the kernel function $K(\boldsymbol{x}, \boldsymbol{x}_i)$. In this paper, Gaussian radial basis function (RBF) kernel function is used for SVM model.

$$K(\boldsymbol{x}, \boldsymbol{x}_i) = \exp(-\gamma\, \|\boldsymbol{x} - \boldsymbol{x}_i\|^2) \tag{7}$$

where, γ is the parameter of RBF.

The values of γ and C are crucial to the modeling of SVM, they influence the prediction performance of SVM model. In this paper, to find the optimal value of the two parameters, particle swarm optimization (PSO) algorithm is involved, and the PSO-SVM model is established such as to obtain better prediction performance.

C. THE COMBINATION OF ARMA AND PSO-SVM MODEL

Different prediction model excels at different aspects and reveals various prediction performance. It is usually difficult to judge a single prediction model arbitrarily. However, it is usually good practice to combine two or three effective prediction models with rational weights such as to prospectively improve the overall wind power prediction performance. The combination of ARMA and PSO-SVM Model for wind power prediction is the integration of time series method and intelligent method, it can retain more valuable information and improve the prediction precision.

Based on ARMA model and PSO-SVM model, the hybrid PSO-SVM-ARMA model can be combined as follows

$$F_{\text{COMB}} = \omega_1 F_{ARMA} + \omega_2 F_{SVM} \tag{8}$$

where, ω_1 and ω_2 are the weight of ARMA model and PSO-SVM model, respectively, satisfying $\omega_1 + \omega_2 = 1$. F_{COMB} is the prediction result of the hybrid PSO-SVM-ARMA model, while F_{ARMA} and F_{SVM} are the prediction results of ARMA and PSO-SVM, respectively.

The covariance minimization method is used to set up the PSO-SVM-ARMA prediction model. It is a modified weight combination solution based on the equal-weight method. The idea of the covariance minimization method is to find a set of optimal weight coefficients $\{\omega_i\}$, such that (9) reach the minimum.

$$Var = \sum_{i}^{M} \omega_i^2 \sigma_i^2 \tag{9}$$

where, σ_i^2 is the variance of the i^{th} specific prediction model. To obtain the optimal weights, the training process of the weights are solved by PSO method.

D. THE MODELING PROCESS OF PSO-SVM-ARMA MODEL

To obtain the hybrid PSO-SVM-ARMA model, the ARMA and PSO-SVM models are first trained, and parameters are estimated and optimized to ensure a feasible prediction precision. The modeling flow chart is shown in Fig. 1.

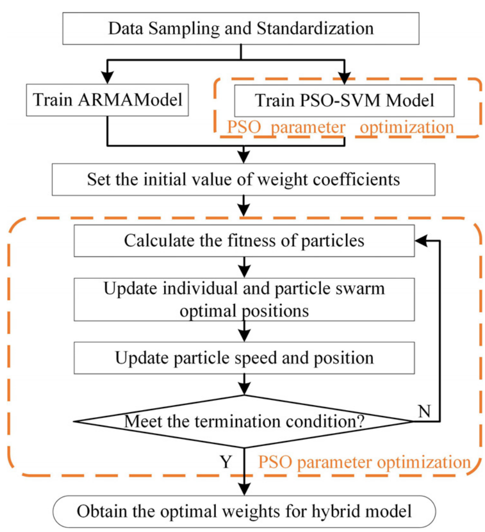

FIGURE 1. The modeling flow chart of PSO-SVM-ARMA.

As illustrated in Fig. 1, in the PSO-SVM model, PSO is used for the optimization of penalty factor and parameter of Kernel function; while in the hybrid PSO-SVM-ARMA model, PSO is effective used for weight optimization.

III. CLUSTERED HYBRID WIND POWER PREDICTION MODEL

Taking into account the intermittent and stochastic characteristics of wind power, it is good practice to investigate on the time series of historical data, and explore better ways to improve the prediction precision. Wind speed and temperature play an important role of the wind power output, and they show different characteristics through the year. To capture the comprehensive characteristics of wind speed, temperature and wind power, the clustering theory is involved such as to examine the effective dataset for wind power prediction. Based on the hybrid prediction model named as PSO-SVM-ARMA model and the clustering theory, the clustered hybrid C-PSO-SVM-ARMA model is proposed in this section to obtain more accurate prediction results.

A. THE CLUSTERED HYBRID PREDICTION MODEL

Specifically, in the clustered hybrid C-PSO-SVM-ARMA prediction model, based on the historical data, the dataset $X = \{x_1, x_2, \ldots, x_{52}\}$ with $x_i = \{\mathrm{WP}_i, \mathrm{WS}_i, \mathrm{WT}_i\}$ is calculated for a wind farm in one year, where WP_i, WS_i and WT_i are the average wind power, wind speed and temperature of the i^{th} week, respectively. With the implementation of clustering theory, the historical data of one year is divided into multiple clusters according to different characteristics at different time periods, and the hybrid prediction model is trained in each cluster with different parameters. The modelling and prediction process of C-PSO-SVM-ARMA model is illustrated in Fig. 2.

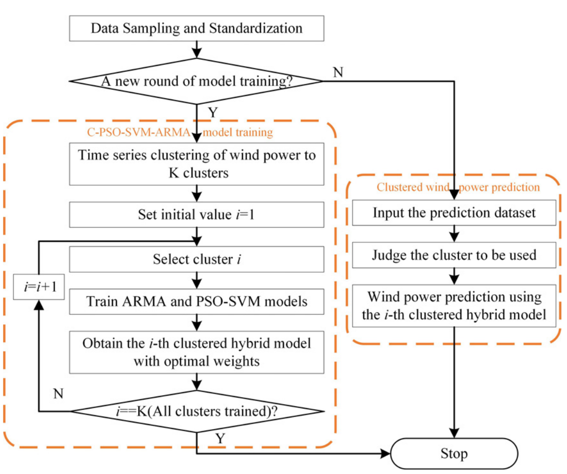

FIGURE 2. The modeling process of C-PSO-SVM-ARMA model.

As shown in Fig.2, in the process of modelling, the parameters of ARMA model, PSO-SVM models and the optimal weights of PSO-SVM-ARMA model for each cluster are estimated, and the K hybrid PSO-SVM-ARMA models with different model estimation constitute the C-PSO-SVM-ARMA model.

When wind power prediction is required, first, the cluster is judged to which the predicted data belongs, then the historical data are used as input into the corresponding clustered hybrid model for prediction.

The C-PSO-SVM-ARMA model can realize that the characteristics of the training dataset are similar to those of the predicted dataset based on clustering theory, and the effective dataset for prediction can ensure the prediction accuracy, while the computation complexity of the prediction algorithm is acceptable.

B. DATA SELECTION AND STANDARDIZATION

ARMA model uses the historical wind power dataset to train data and forecast, while PSO-SVM model uses both the historical wind power data and the relevant meteorological data to train model and forecast.

The wind power output is related to the wind speed, temperature, air density and air pressure. Taking into account that the air density and air pressure are relatively stable in one day, it is not involved in this study. In this work, wind power, wind speed and temperature are considered for the training of PSO-SVM model.

The historical data for ARMA prediction model need to be standardized for the first step. The original dataset are transformed to be the standard dataset with mean value 0 and variance 1 by linear translation transformation. The transformation formula is

$$x_s = \frac{x_o - \mu}{\sigma} \tag{10}$$

where, $\{x_s\}$ is the standardized dataset, and $\{x_0\}$ is the original dataset with mean $= \mu$ and variance $= \sigma^2$.

Similarly, the original wind power, wind speed and temperature data for PSO-SVM prediction model are treated to be the standardized data within [0,1] following (11)

$$\tilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{11}$$

where, $\{\tilde{x}_i\}$ is the standardized dataset, and $\{x_i\}$ is the original dataset with $x_{\max}$ and $x_{\min}$ as the maximum and minimum value of $\{x_i\}$.

C. EVALUATION INDICES OF OVERALL MODELS

In this work, the evaluation indices for wind power prediction verification [22] are used including root mean squared error (RMSE), mean absolute percentage error (MAPE), R^2 and mean absolute error (MAE) as shown in (12)-(15).

$$RMSE = \frac{1}{P_N}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2} \times 100\% \tag{12}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{13}$$

$$R^2 = \frac{\sum_{i=1}^{N} (\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_i)^2} = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_i)^2} \tag{14}$$

$$MAE = \frac{1}{P_N N} \sum_{i=1}^{N} |y_i - \hat{y}_i| \times 100\% \tag{15}$$

where, N is the number of prediction points, $\hat{y}_i, y_i$ are the predicted value and true value of the i^{th} point, respectively. $\bar{y}$ is the mean value of time series, P_N is the value of rated wind power. RMSE can indicate the volatility condition of the prediction error. MAPE and MAE can reflect the precision of prediction. R^2 is the determination coefficient of the prediction model, it lies the range of [0,1], a larger R^2 indicates a higher credibility of the model. The comprehensive employment of the indices can evaluate the wind power prediction models from the viewpoint of stability, credibility and precision.

IV. CASE STUDY

In this study, the testing data is from the wind integration datasets of NREL [22], which contains a consistent set of wind data of more than 30000 sites over United States. Wind power from wind farms with SiteID 49544 and 72428 in 2011 and 2012 are employed. In the wind farms, the sampling frequency of 15-minute is applied, and the rated wind power is 16MW. The ARMA, PSO-SVM, PSO-SVM-ARMA and C-PSO-SVM-ARMA models are all examined by carrying out a 24-hour wind power prediction with 96 prediction points.

A. PARAMETER ESTIMATION OF ARMA MODEL

Based on the standardization method for time series in the last Section, H_0 test and the order selection of ARMA model is calculated as shown in Table. 1.

TABLE 1. The order selection of ARMA model.

p	q	AIC	Test	p	q	AIC	Test
1	1	-4.0306	1	4	3	-4.0469	1
1	2	-4.0391	1	4	4	-4.0468	1
1	3	-4.0455	1	4	5	-4.0462	1
1	4	-4.0450	1	5	1	-4.0469	1
1	5	-4.0458	1	5	2	-4.0473	1
2	1	-4.0483	1	5	3	-4.0467	1
2	2	-4.0478	1	5	4	-4.0464	1
2	3	-4.0465	1	5	5	-4.0458	1
2	4	-4.0464	1	6	1	-4.0476	1
2	5	-4.0468	1	6	2	-4.0465	1
3	1	-4.0479	1	6	3	-4.0460	1
3	2	-4.0471	1	6	4	-4.0458	1
3	3	-4.0468	1	6	5	-4.0452	1
3	4	-4.0472	1	7	1	-4.0466	1
3	5	-4.0464	1	7	2	-4.0460	1
4	1	-4.0471	1	7	3	-4.0453	1
4	2	-4.0471	1	7	4	-4.0469	1

For the whole process of (p, q) order selection, χ^2 test is carried out, and all the models with different pairs of (p, q) order in Table. 1 passed the test.

It can be concluded from Table. 1 that the minimum AIC value can be obtained when $p = 2$, $q = 1$. As a result, the ARMA time series wind power prediction model is ARMA(2, 1).

Least square estimation method is used for parameter estimation with a minimum of the sum of the square of residuals. Parameter estimation result is $(a_1, a_2, b_1) = (1.768, 0.772, -0.680)$, consequently, the ARMA(2,1) model is expressed as

$$WP_t = 1.768WP_{t-1} - 0.772WP_{t-2} + 0.680\varepsilon_{t-1} + \varepsilon_t \tag{16}$$

B. THE PREDICTION RESULTS OF PSO-SVM PREDICTION MODEL AND THE HYBRID PSO-SVM-ARMA MODEL

To set up the PSO-SVM model, 4 points ahead of the predicted point are used, as a result, the input vector $\boldsymbol{x}_t$ include wind power, wind speed and temperature, and the output vector $\boldsymbol{y}_t$ can be expressed as

$$\begin{cases} \boldsymbol{x}_t = \begin{pmatrix} WP_{t-1}, \ldots, WP_{t-4}, WS_{t-1}, \ldots, \\ WS_{t-4}, WK_{t-1}, \ldots, WK_{t-4} \end{pmatrix} \\ \boldsymbol{y}_t = WP_t \end{cases} \tag{17}$$

where, WP_t is the wind power data, WS_t is the wind speed data and WK_t represents the temperature data. Wind speed and temperature time series are depicted in Fig.3.

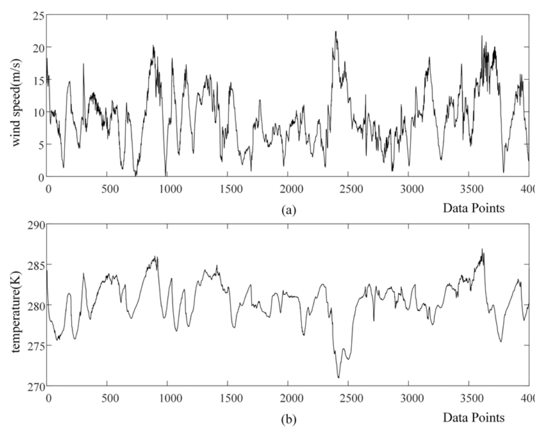

FIGURE 3. The time series of (a) wind speed and (b) temperature.

For PSO-SVM model, the Gaussian RBF function parameter $\gamma \in [1, 100]$ and $C \in [1, 5]$ are given. To train the PSO-SVM model, the RMSE index value is selected to train the particle fitness, the particle population of PSO is 30, and the maximum iteration is 100. In PSO-SVM model, the convergence process of PSO is illustrated in Fig. 4, and the estimated parameters are (C, γ) = (1.000, 1.242).

Furthermore, the hybrid PSO-SVM-ARMA model is trained, the optimal weights are obtained based on the PSO method with $\omega_1 = 0.492$ and $\omega_2 = 0.508$. In PSO-SVM-ARMA model, the convergence process of PSO is reported in Fig. 4.

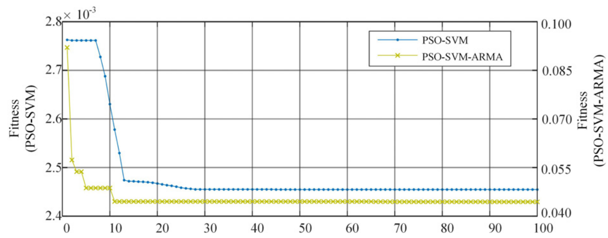

FIGURE 4. The convergence curves of PSO fitness in two models.

In addition, the prediction errors are calculated based on the above mentioned three models and the RMSE, MAPE, R^2 and MAE results are listed below.

It can be found from Table. 2 that:

TABLE 2. The evaluation indices of three models.

Prediction Model	RMSE(%)	MAPE(%)	R^2	MAE(%)
ARMA	5.50	10.57	0.90	3.94
PSO-SVM	5.38	10.38	0.92	3.69
PSO-SVM-ARMA	5.38	10.31	0.94	3.63

(1) The predicted time series is relatively stable, and all of the prediction models obtained acceptable prediction error.

(2) The hybrid PSO-SVM-ARMA model has the lowest RMSE, MAPE and MAE, and it shows the highest R^2. PSO-SVM-ARMA model improves the overall prediction performance.

The prediction error of ARMA, PSO-SVM and PSO-SVM-ARMA models is depicted in Fig. 5.

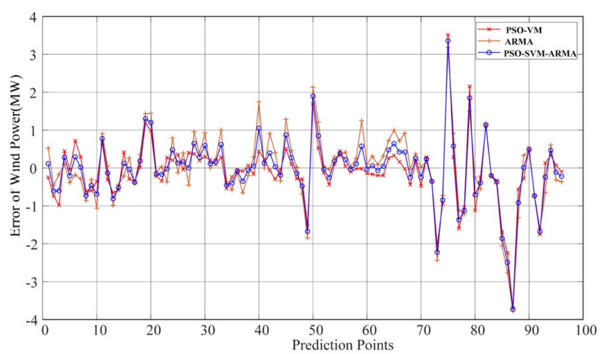

FIGURE 5. The prediction errors of the three models.

It can be graphically found from Fig. 5 that the PSO-SVM-ARMA model can decrease the overall prediction error. Specifically, it can counteract the positive and negative error of ARMA and PSO-SVM.

Consequently, the PSO-SVM-ARMA model is further utilized in the following analysis.

C. THE PREDICTION RESULTS OF C- PSO-SVM-ARMA MODEL

In this part, C-PSO-SVM-ARMA prediction model is examined with the basis of PSO-SVM-ARMA model.

Based on the historical wind power, wind speed and temperature of the two wind farms in 2011 and 2012, four weekly average datasets can be obtained. The clustering theory is carried out for the four datasets respectively, and 3 clusters are obtained as shown in Fig. 6. It can be concluded that the data of week 1∼ 9, week 32∼ 40 are clustered as type I cluster, and week 10∼31 are clustered as type II cluster, and week 41∼ 52 are clustered as type III cluster. Parameter estimation for each cluster of C-PSO-SVM-ARMA model is carried out and the parameters are listed in Table. 3.

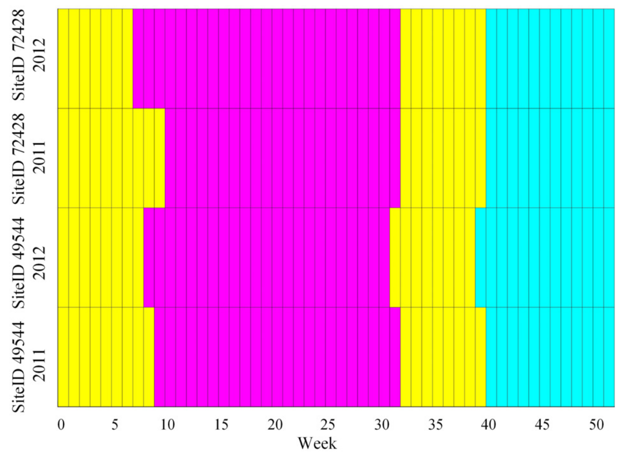

FIGURE 6. The clustering results of time series.

In addition, the C-PSO-SVM-ARMA model is compared with two other hybrid models to verify prediction precision and computation efficiency. The implementation of the two models is carried out as follows:

a) PSO-SVM-ARMA model: The parameters of this model are obtained based on the historical wind power, wind speed, and temperature data in 2011, and the historical data of 2012 are used as input to predict wind power for different clusters.

b) I-PSO-SVM-ARMA model: The historical data ahead of the prediction day within the same cluster including wind power, wind speed, and temperature are used to instantly train the hybrid PSO-SVM-ARMA model. Parameters need to be trained and updated for each wind power prediction.

The prediction results of the three hybrid models for cluster I are graphically reported in Fig. 7.

The evaluation indices including RMSE, MAPE, R^2 and MAE are further employed for comparison of the three hybrid models. The RMSE of the three hybrid models are summarized in Table. 4, RMSE of each cluster and the mean of RMSE are all reported.

According to Table. 4, I-PSO-SVM-ARMA and C-PSO-SVM-ARMA models are comparable for each cluster, and they are overall better than PSO-SVM-ARMA model from the comparison of mean value of RMSE.

The evaluation for the three hybrid models by means of MAPE are summarized and compared in Table. 5.

TABLE 3. Parameter estimation for C-PSO-SVM-ARMA model.

Parameter		Cluster I	Cluster II	Cluster III
	(p, q)	(10, 3)	(8, 3)	(10,4)
ARMA	$(a_1,\ldots,a_p)$	(-0.892, -0.789, 0.277, 0.462, -0.066, 0.022, 0.062, -0.051, -0.090, 0.067)	(-1.060, 0.126, 0.393, -0.409, 0.028, -0.032, 0.012, -0.034)	(-0.872, -0.120, -0.517, 0.195, 0.288, 0, 0.046, -0.025, 0.064, -0.055)
	$(b_1,\ldots,b_q)$	(0.247, -0.663, -0.381)	(-0.056, 0.010, 0.404)	(0.139, -0.048, -0.403, -0.272)
PSO-SVM	(C, γ)	(1.000, 0.930)	(8.828, 0.838)	(2.801, 0.901)
C-PSO-SVM-ARMA	(ω_1, ω_2)	(0.615, 0.385)	(0.563, 0.437)	(0.582, 0.418)

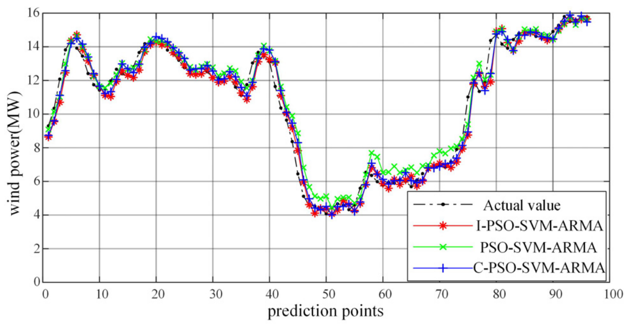

FIGURE 7. The prediction results of three different hybrid models for cluster I.

TABLE 4. The RMSE comparison among the three hybrid models (%).

Model	Cluster I	Cluster II	Cluster III	Mean Value
C-PSO-SVM-ARMA	3.88	5.19	5.56	4.88
I-PSO-SVM-ARMA	4.00	4.81	5.50	4.75
PSO-SVM-ARMA	4.63	5.69	5.56	5.25

TABLE 5. The MAPE comparison among the three hybrid models (%).

Model	Cluster I	Cluster II	Cluster III	Mean Value
C-PSO-SVM-ARMA	4.68	8.04	10.31	7.68
I-PSO-SVM-ARMA	4.70	6.74	10.13	7.19
PSO-SVM-ARMA	6.82	9.26	10.24	8.77

According to Table. 5, similar conclusion can be found as that of Table. 4, I-PSO-SVM-ARMA and C-PSO-SVM-ARMA models are overall better than PSO-SVM-ARMA model from the comparison of mean value of MAPE.

Moreover, the prediction errors by means of R^2 and MAE for the three hybrid models are summarized and compared in Table. 6 and Table. 7, respectively. The graphical illustration of evaluation index comparisons is reported in Fig.8.

Larger R^2 values show better credibility of prediction models. From Table. 6, the three models are all credible, while I-PSO-SVM-ARMA and C-PSO-SVM-ARMA models are better than PSO-SVM-ARMA model.

TABLE 6. The R^2 comparison among the three hybrid models.

Model	Cluster I	Cluster II	Cluster III	Mean Value
C-PSO-SVM-ARMA	0.97	0.88	0.95	0.93
I-PSO-SVM-ARMA	0.97	0.90	0.95	0.94
PSO-SVM-ARMA	0.96	0.85	0.95	0.92

TABLE 7. The MAE comparison among the three hybrid models (%).

Model	Cluster I	Cluster II	Cluster III	Mean Value
C-PSO-SVM-ARMA	2.81	4.06	3.69	3.50
I-PSO-SVM-ARMA	2.81	3.50	3.56	3.31
PSO-SVM-ARMA	3.56	4.63	3.63	3.94

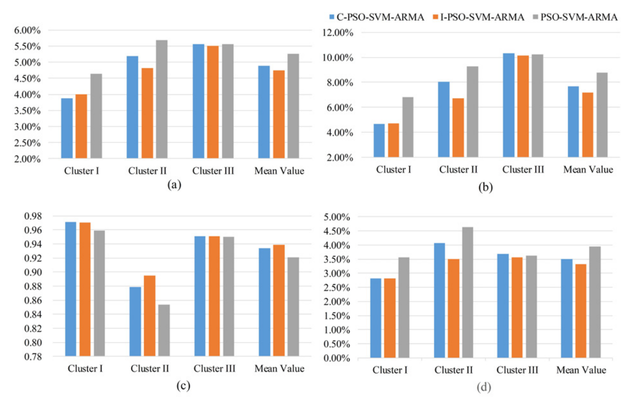

FIGURE 8. The graphical comparison of (a) RMSE, (b) MAPE, (c) R^2 and (d) MAE among the three hybrid models.

From Table. 7, I-PSO-SVM-ARMA and C-PSO-SVM-ARMA models are obviously better than PSO-SVM-ARMA model. Nevertheless, the three models all exhibit good prediction performance from this aspect.

It can be safely concluded from this case study that:

a) The three hybrid models all reveal satisfying prediction performance. In addition, the C-PSO-SVM-ARMA model is overall better than the before proposed PSO-SVM-ARMA model. This indicates the effectiveness of clustering process and also shows that the clustered model can further provide better prediction performance.

b) The mean value of RMSE, MAPE and MAE of I-PSO-SVM-ARMA model are all similar to that of the proposed C-PSO-SVM-ARMA model, and all are a little smaller than that of C-PSO-SVM-ARMA model. The mean value of R^2 of I-PSO-SVM-ARMA model is larger than that of C-PSO-SVM-ARMA model. This indicates that I-PSO-SVM-ARMA model shows better performance than C-PSO-SVM-ARMA model to some degree.

c) However, the computation efficiency is further compared between I-PSO-SVM-ARMA model and C-PSO-SVM-ARMA model. For wind power prediction in the same time period/cluster, C-PSO-SVM-ARMA model needs only perform model training once, while I-PSO-SVM-ARMA needs to re-train the model every time for each 96-point wind power prediction. Actually, the computation time cost of I-PSO-SVM-ARMA model is 8∼10 times of C-PSO-SVM-ARMA model.

As a result, C-PSO-SVM-ARMA model shows great advantage and is highlighted as a feasible model with low computation time and satisfying prediction precision.

V. CONCLUSION

In this paper, several wind power prediction models are discussed and examined, and the C-PSO-SVM-ARMA model is proposed to improve the prediction performance of wind power.

With the combination of time series method and intelligent method, the hybrid model named PSO-SVM-ARMA model with optimal weights is illustrated and verified as a capable model in wind power prediction compared with single prediction models, and PSO method plays a positive role for parameter optimizations.

Based on the clustering theory and the hybrid PSO-SVM-ARMA model, the effective dataset for wind power prediction are examined, and the C-PSO-SVM-ARMA wind power model is prospective proposed to obtain satisfying prediction results of wind power. Case study show that the C-PSO-SVM-ARMA model can reduce the time of model training and ensure the prediction precision. The prediction results of C-PSO-SVM-ARMA model is feasible to provide reference to the stable and safe operation of power system with large-scale integration of wind power.

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