Short Term Load Forecasting Using A Hybrid Model Based On Support Vector Regression

Aliasghar Baziar, Abdollah Kavousi-Fard

Abstract: This paper proposes a new hybrid method based on support vector regression (SVR) to predict the load value of power systems accurately. The proposed method will use the SVR to overcome some deficiencies such as overfitting and complicated structure that exist in the neural network. In order to find the optimal values of the parameters, krill herd (KH) algorithm is used as the optimizer. The KH algorithm can explore the problem search space for reaching the best structure for the SVR when training. In order to check the performance and accuracy of the proposed hybrid method, the empirical load data from the Fars Regional Company are used as the test data. The simulations show the high reliable and accuracy of the proposed method.

Index Terms: Support Vector Regression (SVM), Krill Herd (KH) Algorithm, Short Term Load Forecasting (STLF).

1 INTRODUCTION

Precise load forecasting problem is a precarious subject to make use of the limited energy sources with the maximum efficacy. In the area of energy increment and power systems operation or planning, overestimation of the load value can result in overconservative operation (unnecessary energy acquisition) while underestimation would give rise to overrisky operation (Operating in susceptible area) [1]. By definition, short term load forecasting (STLF) fit in the time horizon of one hour to one week [2]. Understanding the reputation of proper load forecasting created numerous explorations in latest years to reach more reliable forecasting devices. Theoretically, STLF techniques are classified into two chief categories [3]: 1) statistical or parametric models & 2) artificial intelligence techniques. Amongst the greatest statistical models, time series (autoregressive moving average models) [4], regression models (linear or piecewise-linear) [5], data mining approaches [6], Kalman filter [7], and state space method [8-9] are prominent. In the time series models, the utmost prevalent is ARIMA model. Nevertheless, with the high complexity of the new forecast data such as power system load consumption, these techniques are not a yet reliable method anymore. Therefore, the transition from the linear models to the nonlinear models seems necessary. In the class of artificial intelligence based techniques, genetic algorithms (GAs) [10], expert systems [11], artificial neural networks (ANNs) [12], Fuzzy systems [13], Neuro-Fuzzy systems [14] and support vector regression (SVRs) [15] are noticeable. Among these techniques, SVR is the most successful method since it could overcome some deficiencies that exist in the other methods. For example, in the face of complex data, the ANN structure becomes complicated and thus the overfitting phenomenon will happen. Similarly, the fuzzy based methods require the experience of experts for modeling the load data [16-18]. The SVR model uses the structural risk minimization (SRM) idea in place of empirical risk minimization (ERM) (in ANN) to decline an upper bound on the simplification error. Some of the applications of SVR can be found in financial problems [19], software reliability forecasting [20], wind speed forecasting [21], rainfall forecasting [22] and electrical load [23]. According to the above discussion, this paper proposes a new forecast model based on SVR to model the nonlinear behavior of the load value in the power systems. In order to reach the most efficiency, the parameters of the SVR should be adjusted. In this way, a new optimization algorithm based on krill herd (KH) is proposed to find the optimal values of the kernel function parameter as well as the hyper plane parameters. KH algorithm is a metahuristic optimization algorithm that mimics the behavior of krill animals in the sea [24]. KH is constructed using the crossover and mutation operators from the GA and thus can be a reliable method in comparison to other evolutionary algorithms. The proposed hybrid method shows a hybrid procedure for first training the SVR using the KH and then using it for modeling any nonlinear data. In order to check the performance of the proposed hybrid method, the practical load data of 400 kV substation of Fars Regional Company in 2009 are used.

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2. Support Vector Regression

The term SVR model is constructed using its capability to model the nonlinearity of the data in the higher dimension. In order to describe the SVR model, suppose the input data $\{(x_i, y_i)\}^N$ in which *N* is the number of the training points. One nonlinear mapping φ (.) from the input space to a new space with a higher dimension is stated as $\varphi(.):\Re^n \rightarrow \Re^{n_h}$. Theoretically, it is proved that there is a linear function *f* in the higher dimension that can learn the nonlinear relationship between the input and output data. The linear function *f* is called SVR as follows:

$$f(x) = W^T \varphi(x) + b \quad (1)$$

Where *W* ($W \in \Re^{n_h}$) and *b*($b \in \Re$) are adjusting parameters of the SVR function. The coefficient *W* and *b* are calculated using the below optimization:

$$\min \ R_{SVR} = \frac{1}{N}\sum_{i=1}^{N} \Theta_{\varepsilon}(y_i, W^T \varphi(x_i) + b) \quad (2)$$

Where $\Theta_{\varepsilon}(y_i, f(x_i))$ is the ε-insensitive loss function as follows:

$$\Theta_{\varepsilon}(y, f(x)) = \begin{cases} | f(x) - y | - \varepsilon \; ; & | f(x) - y | \geq \varepsilon \\ 0 \; ; & \text{Else} \end{cases} \tag{3}$$

Once SVR tries to diminish the overhead equation by reducing the training error, it will explore for the best hyper plane too (as shown in Fig. 1). This mixture is formulated as follows:

$$Min_{W,b,\xi*,\xi} R_{\varepsilon}(W, \xi*, \xi) = \frac{1}{2} W^T W + C \sum_{i=1}^{N} (\xi_i * + \xi_i) \tag{4}$$

In the above equation, the first term stops big weighting factors when preserving the regression function flatness. The second term reprimands the training error by the use of ε-insensitive loss function. Likewise, *C* is the balance constant to exchange two terms. According to Fig. 1, ξ_i is the training error bellow –ε and $\xi_i *$ is the training error above the + ε. The resultant constraints are as follows:

$$\begin{aligned} & y_i - W^T \varphi(x_i) - b \leq \varepsilon + \xi_i^* && ; i = 1, ..., N \\ & -y_i + W^T \varphi(x_i) + b \leq \varepsilon + \xi_i && ; i = 1, ..., N \\ & \xi_i^* \geq 0 && ; i = 1, ..., N \\ & \xi_i \geq 0 && ; i = 1, ..., N \end{aligned} \tag{5}$$

The value of *W* can be evaluated as follows:

$$W = \sum_{i=1}^{N} (\beta_i^* - \beta_i) \varphi(x_i) \tag{6}$$

Where β_i^* and β_i are Lagrangian multipliers. Now, the SVR function is reformulated in the dual space as below:

$$\begin{aligned} & f(x) = \sum_{i=1}^{N} (\beta_i^* - \beta_i) K(x_i, x) + b \\ & K(x_i, x) = \varphi(x_i) \circ \varphi(x_j) \end{aligned} \tag{7}$$

where $K(x_i,x)$ is the kernel function. It may be useful to say that any function which satifies Mercer's condition [25] can be utilized as the kernel function. Also, the kernel function is computed by the inner product of $\varphi(x_i)$ and $\varphi(x_j)$. Among different types of kernel functions, Gaussian radial basis function (RBF) as the result of simple implementation, ability of nonlinear mapping is the most popular. The RBF function is mathematically shown as below:

$$K(x_i, x_j) = \exp(-0.5 \| x_i - x_j \|^2 / \sigma^2) \tag{8}$$

Where σ is the standard deviation parameter.

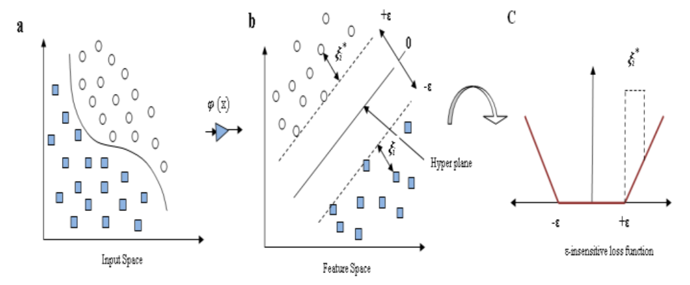

Fig. 1. *The conceptual illustration of SVR model: a) data input in the original nonlinear input space, b) conversion to a linear problem in a higher dimension problem & 3) ε-insensitive loss function*

3. Krill Herd Algorithm

This section describes the KH algorithm as a powerful optimization algorithm. KH was introduced first in 2012 as a nature inspired optimization method that mimics the behavior of krill search for the food [24-25]. In comparison to other algorithms such BA [26], CSA [27-29], HS [30-31], FA [32-34], TLBO [35-36], CA [37], HBMO [38-42], PSO [43-44] and fuzzy [46]; KH algorithm is simple, has fast convergence ability and provides proper balance between the local and global searches. The main structure of the KH algorithm can be formulated using three ideas of: 1) induction, 2) foraging and 3) random diffusion that are explained below:

***- Induction movement*:** This movement simulates the impact of dissimilar krill on each other. It is evident that the greatest consequence is induced by the nearby krill. In this way, the speed of i^{th} krill at m^{th} iteration is modernized like this [25]:

$$V_{ind,i}^{m} = \alpha_{ind,i} V_{ind,i}^{\max} + \omega_{ind} V_{ind,i}^{m-1} \tag{9}$$

$$\begin{aligned} \alpha_{ind,i} = & \sum_{j=1}^{N_s} \left[\frac{f_i - f_j}{f_w - f_b} \times \frac{X_i - X_j}{|X_i - X_j| + \varepsilon} \right] + \\ & 2 \left[rand(.) + \frac{i}{Iter_{\max}} \right] f_i^b X_i^b \end{aligned} \tag{10}$$

Where $\alpha_{ind,i}$ is attractive/repulsive tendency factor , V_{ind}^{max} is maximum induced velocity , ω_{ind} is inertia of induction and ε is small positive number. Also, $Iter_{max}$ is maximum iteration and rand is a random number. The krill X_j is in the adjacent distance of krill X_i if it is inside this radius [25]:

$$R_{Vicinity} = \frac{1}{5N_p} \sum_{j=1}^{N_p} |X_i - X_j| \tag{11}$$

where N_p is Number of the number of population.

***- Foraging movement*:** This movement simulates the effort of the krill for finding food based on their last experiences and the location of the food as follows [17]:

$$V_{frg,i}^{m} = 0.02[2(1-\frac{i}{Iter_{\max}})f_i \frac{\sum_{i=1}^{N_s} \frac{X_i}{f_i}}{\sum_{i=1}^{N_s} \frac{1}{f_i}} + f_i^b X_i^b] + \omega_{frg} V_{frg,i}^{m-1} \quad (12)$$

where $V_{frg,i}^{m}$ is foraging velocity of *i*th krill at *m*th movement, ω_{frg} is the inertia of foraging motion.

***- Diffusion movement*:** This movement simulates a random distributed drive for the krill as follows:

$$V_{diff,i}^{m} = \upsilon \times \omega_{diff} \quad (13)$$

Here υ is distributed uniformly [-1, 1] and ω_{frg} is the inertia of diffusion motion. According to the above three movements, the position of the krill population can be renewed as follows:

$$X_i^{m+1} = X_i^m + V_{r,i}^m \kappa \sum_{j=1}^{N_v} (u_j - l_j)$$
$$V_{r,i}^m = V_{ind,i}^m + V_{frg,i}^m + V_{diff,i}^m \quad (14)$$

Where N_v is the number of krill in the surrounding distance and u_j / l_j is upper/lower bound of j^{th} control variable. The surrounding distance for each krill is shown in Fig. 2. Also, the flowchart of the KH algorithm is shown in Fig. 3.

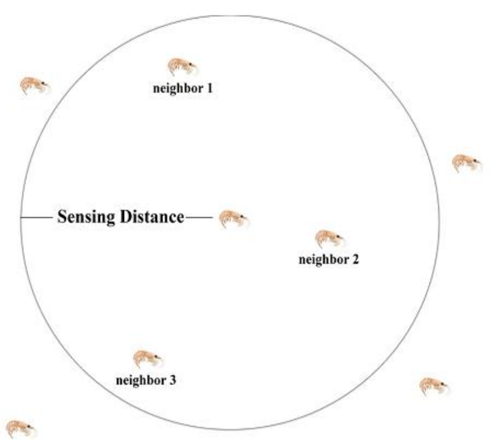

Fig. 2: *Schematic diagram of sensing distance around each krill.*

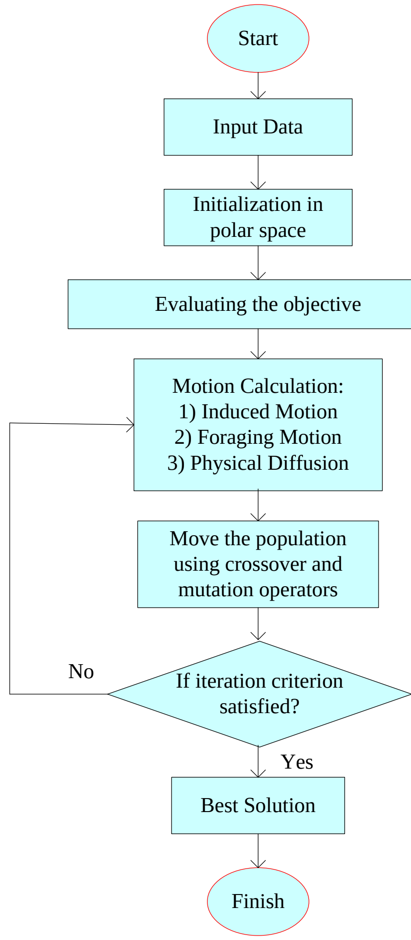

Fig. 3: *Flowchart of KH algorithm.*

4. Application Procedure

The below steps are required to solve the proposed problem:

1- Input data including the load sample data, SVR parameters, the KH data such as the size of population and the termination criterion.

2- Generate the initial KH population. The optimal values of the SVR parameters including the kernel function (σ) and the optimal hyper plane parameters (C & ε) are determined by KH. Therefore, each krill is an individual that shows the optimal value for the SVR parameter as follows:

$$X_i = [C, \varepsilon, \sigma] \quad (15)$$

3- Calculate the fitness function for the krill. In order to see the satisfying performance of the proposed method over the other well-known methods in the area, the below criteria are utilized. Here N_{es} is the number of data which is predicated.

- Relative percentage error:

$$\Delta_i \% = \frac{|\tilde{y}_i - y_i|}{y_i} \times 100, i = 1, 2, ..., N_{es} \quad (16)$$

- Mean absolute percentage error (MAPE):

$$MAPE\% = \frac{1}{N_{es}} \sum_{i=1}^{N_{es}} \Delta_i \tag{17}$$

- Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{N_{es}} \sum_{i=1}^{N_{es}} \Delta_i^2} \tag{18}$$

- Mean absolute error (MAE):

$$MAE = \frac{1}{N_{es}} \sum_{i=1}^{N_{es}} \left| \tilde{y}_i - y_i \right| \tag{19}$$

- Maximum absolute relative percentage error (MARPE):

$$MARPE = max(100 \times \frac{\left| \tilde{y}_i - y_i \right|}{y_i}), i = 1, 2, ..., N_{es} \tag{20}$$

In this paper, MAPE is used as the forecast criteria.

4- Choose the best krill as X^b and store it. The best krill is the one with the least value of MAPE.

5- Update the krill population using the three steps describes in the last part.

6- Update the position of X^b.

7-Check the termination criterion, if satisfied finish the algorithm. Otherwise, return to step 5.

5. Simulation Results

In this section, the performance of the proposed hybrid method is examined using the practical data samples from the Fars Regional Power Company. In this way, the data are divided into three parts of 1) training data, 2) validation data and 3) test data. The data belong to the 2009 [46]. For showing the appropriate performance of the proposed hybrid method, the results of other methods such as ARIMA, ANN and SVR (alone) and SVR-PSO are calculated and shown here. The input data set is the day-to-day peak load of eight weeks earlier the forecasting day. The test data is the last month of the data sample. All the simulation results are implemented in MATLAB 7.10.0 software on a Pentium-IV 2.67-GHz personal computer. It is worth noting that after the optimization, the optimal values of the SVR parameters are C=672, ε=0.23 and σ =0.806. Here, the termination criterion is assumed to be 100 iterations to avoid high computational burden. Table 1 shows the relative percentage error (Δ) for different methods. As it can be seen from Table 1, the proposed hybrid method has reached to lower percentage error in most of the forecast days.

Table 1. *Comparison of Relative Percentage Error (Δ) for Different Methods*

Day	ARIMA model $\Delta_i\%$	ANN $\Delta_i\%$	SVR $\Delta_i\%$	SVR-PSO $\Delta_i\%$	The Proposed Hybrid Method
1	2.233	0.879	1.992	1.4614	1.2747
2	0.089	1.362	1.200	3.4033	1.8028
3	1.850	2.425	0.805	2.5701	1.8901
4	4.220	2.100	1.427	1.5273	1.1232
5	2.430	1.702	0.922	1.6614	1.2218
6	2.110	2.614	0.898	2.5068	1.8436
7	3.580	2.726	0.858	1.7150	1.2613
8	0.743	7.825	0.125	4.1528	2.8541
9	6.854	3.044	8.336	0.2484	0.9327
10	2.189	0.079	6.079	2.8603	2.1035
11	1.998	1.242	1.369	0.1332	0.4803
12	1.053	6.892	1.472	1.5950	1.1730
13	6.410	0.162	1.732	4.1190	2.1292
14	0.493	0.541	1.266	1.9911	1.4643
15	2.397	2.849	3.036	0.6239	0.9588
16	3.918	3.726	2.165	1.3919	1.1236
17	5.146	1.003	0.379	0.0712	0.2224
18	0.900	0.183	0.507	3.3918	1.4944
19	0.355	0.237	3.170	0.7443	0.5474
20	1.016	1.264	1.183	0.2831	0.3082
21	0.755	0.854	2.803	0.9391	0.6906
22	3.322	3.283	1.156	0.5913	0.4349
23	3.774	3.068	3.685	0.7931	0.8833
24	3.943	1.947	0.368	2.8410	1.3893
25	0.989	1.230	0.518	3.9594	1.9118
26	1.112	1.862	0.879	0.2286	0.3681
27	1.485	0.289	0.117	0.7241	0.5325
28	1.123	0.600	0.818	3.0529	1.8351
29	2.789	1.881	0.229	0.7848	0.5771
30	1.789	0.828	4.644	1.7766	1.3065

In Table 2, the simulation results of the forecast criteria are shown comparatively. From this table, it is seen that the proposed method has reached to much better forecast values. From the view of MAPE, low value of the average forecast value demonstrates the high robustness of the method. Also, lower value of RMSE shows the high reliability of the proposed method.

Table 2. *Results of Forecasting Criteria Evaluated by Different Methods*

Method	MAPE (%)	MARPE	RMSE	MAE
ARMA model (Alone)	2.3001	6.8549	2.8731	34.0608
ANN	1.9569	7.8251	2.6396	28.8032
SVR	1.8051	8.3365	2.5667	26.1718
SVR-PSO	1.7381	4.1525	2.1399	24.0145
The Proposed Hybrid Method	**1.27046**	**2.8541**	**1.3618**	**17.9651**

Finally, Fig. 4 shows the forecast curve along with the actual load data value for the last month of the data sample. As it can be seen from this figure, the proposed method could follow the actual load data suitably. Accordingly, the proposed hybrid method can give more dependable results over the other popular forecasting methods such as ARIMA, ANN and SVR model.

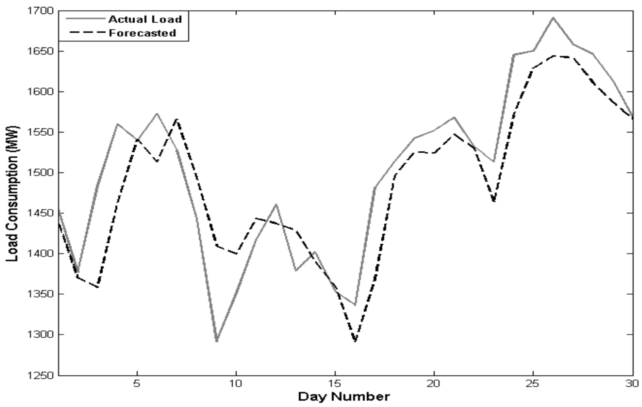

Fig. 4. *Load forecasting results by the proposed hybrid method*

6. Conclusion

This paper proposed a hybrid method based on SVR and KH algorithm to predict the load data with more accuracy. The proposed method uses the KH algorithm to adjust the kernel function (σ) and the optimal hyper plane parameters (C & ε) optimally. Therefore, in the first step, by the use of the training data, the SVR model is trained. Here, the KH algorithm is used in an iterative manner to optimize the SVR parameters. In the second step, the optimized SVR is used for forecasting the load data. The simulation results on the practical sample data shows the high accuracy of the proposed method for forecasting the data. Also, it is deduced that the reliability and robustness of the proposed method is more demanding than the other method. Last but not least, the computational burden of the proposed method effectively nothing.

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