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ORIGINAL ARTICLE

Short Term Load Forecasting Model Based on Kernel-Support Vector Regression with Social Spider Optimization Algorithm

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Abstract
Short-term load forecasting in power system is an important factor planning and electricity marketing. Due to the uncertainty of the load demand, many studies have been devised for nonlinear prediction methods. In this paper, a hybrid approach consisting of support vector regression (SVR) and social spider optimization (SSO) is proposed for short term load forecasting. The SVR technique has proven to be useful in nonlinear forecasting problems. To improve accuracy of SVR parameters are tuned using SSO. The SSO algorithm is based on the simulation of cooperative behavior of social-spiders and helps in achieving good results.

Keywords Short term load forecasting · Kernel · Support vector regression · Social spider optimization · EUNITE and New England network

1 Introduction

Short-term load forecasting is one of the most important issues in deregulated power system operation and planning. Many operational decisions in deregulated power systems all around the world, such as unit commitment, automatic generation control and maintenance scheduling, depend on the future behavior of demand loads [1].

In recent years, power system privatization and deregulation, made it necessary to accurately predict STLF [2]. During the previous decades, a wide variety of techniques have been used for the problem of STLF [3]. In recent decade, many machine learning techniques have been developed, such as the support vector machines (SVMs) [4]. SVM have been used for load prediction and electricity price forecasting.

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This method has good performance in prediction. Afterwards SVMs have been developed for regression purposes also. SVR technique is a powerful machine learning, which is based on statistical learning theory and established on the structural risk minimization (SRM) principle. SVR is suitable for prediction because it has a simple structure and need least data base [5]. To get a proper result in SVR, one has to optimize its parameters. Various methods has been proposed to optimize these parameters by researchers, like firefly algorithm [6].

During the past decade, many solutions constrained optimization problems using genetic algorithm, ant colony algorithm, particular swarm optimization algorithms have received considerable attention among researchers. Social spider optimization is a new method to find extremum points [11–15]. The SSO algorithm is a new bio-inspired optimization algorithm based on the simulation of the cooperative behavior of social spiders.

This algorithm considers two different search spiders, males and females. Depending on gender, they have different behavior which can find themselves in the colony based on the biological laws. In SSO approaching obtain optimum results in minimum time used two different orders.

In this paper, SSO for SVR parameters tuning is introduced. The remainder of this paper is as follows. Section 2 present the SVR, kernel functions theory and some background regarding SSO, as well as Sect. 3 explains the solving method. Section 4

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discusses about results of testing two standard data set in SSO–SVR and Sect. 5 states conclusions.

2 Problem Formulation

2.1 The SVR-Based STLF Method

Support vector regression (SVR) for prediction has been popular in the past decade. Many works have addressed this issue but sometimes the SVR formula needed to be modified [16]. This paper presents a rather simple and direct approach to construct such intervals. It is assumed that the climatic conditions and historical load and calendar date of the target value depend on its input only through the predicted value and can propose this distribution by simple functions via SVR to the model.

2.2 Basic Principles of SVR Overview

The regression problem can be stated as:

Given a training data set $D = \{(y_i, t_i) | i = 1, 2, ..., n\}$, of input vectors y_i and associated targets t_i, the goal is to fit a function g(y) which approximates the relation inherited between the data set points and it can be used later on to infer the output t for a new input data point y. Any practical regression algorithm has a loss function $L(t;g(y))$, which describes how the estimated function deviated from the true one. In this paper, Vapnik's loss function is used, which is known as ε insensitive loss function and defined as:Hence the formulation

$$L(t;g(y)) = \begin{cases} 0 \quad if\ |t - g(y)| \le \varepsilon \\ |t - g(y)| - \varepsilon \quad otherwise \end{cases} \tag{1}$$

Figure 1 depicts the situation graphically. The following discussion begins by describing the case of linear functions g, taking the form:

$$f(y) = w.y + b \tag{2}$$

where $w \in Y$, Y is the input space, $b \in R$ and $w.y$ is the dot product of the vectors w and y.

The goal of a regression algorithm is to fit a flat function to the data points. Flatness in the case of Eq. (2) means that one seeks a small w. One way to ensure this flatness is to minimize the norm, i.e. w^2. Thus, the regression problem can be written as a convex optimization problem:

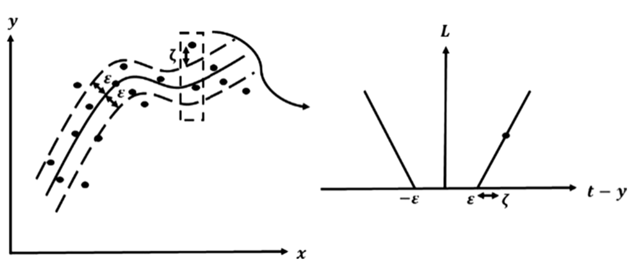

Fig. 1 Margin loss setting for a linear SVM

$$minimize\ \frac{1}{2}w^2 \tag{3}$$

$$Subject\ to \begin{cases} t_i - (w.y + b) \le \varepsilon \\ (w.y + b) - t_i \le \varepsilon \end{cases} \tag{4}$$

Hence the formulation stated in (4) is attained:

$$minimize\ \frac{1}{2}w^2 + C\sum_{i=1}^{n}\left(\zeta_i + \zeta_i^*\right) \tag{5}$$

$$Subject\ to \begin{cases} t_i - (w.y + b) \le \varepsilon + \zeta_i \\ (w.y + b) - t_i \le \varepsilon + \zeta_i^* \\ \zeta_i, \zeta_i^* \ge 0 \end{cases}. \tag{6}$$

The constant $C \ge 0$ determines the trade-off between the flatness of g and the amount up to which deviations larger than ε are tolerated. This corresponds to the so called ε insensitive loss function which was described before. It turns out that in most cases the optimization problem Eq. (6) can be solved more easily in its dual formulation. The minimization problem in Eq. (6) is called the primal objective function. The key idea of the dual problem is to construct a Lagrange function from the primal objective function and the corresponding constraints, by introducing a dual set of variables.

$$\begin{aligned} L = {} & \frac{1}{2}w^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \\ & - \sum_{i=1}^{n}\left(\lambda_i\zeta_i + \lambda_i^*\zeta_i^*\right) \\ & - \sum_{i=1}^{n}\propto_i\left(\varepsilon + \zeta_i - t_i + (w.y + b)\right) \\ & - \sum_{i=1}^{n}\propto_i^*\left(\varepsilon + \zeta_i^* + t_i + (w.y + b)\right). \end{aligned} \tag{7}$$

Here L is the Lagrangian and $\propto_i, \propto_i^*, \lambda_i$ and λ_i^* are Lagrange multipliers. Hence the dual variables in Eq. (7) have to satisfy positivity constraints:

$$\propto_i, \propto_i^*, \lambda_i, \lambda_i^* \ge 0 \tag{8}$$

It follows from the saddle point condition that the partial derivatives of L with respect to the primal variables $\left(w, b, \zeta_i, \zeta_i^*\right)$ have to vanish for optimality:

$$\frac{\partial L}{\partial b} = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) = 0, \frac{\partial L}{\partial w} = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) y_i = 0, \frac{\partial L}{\partial \zeta_i^{(*)}} = C - \alpha_i^{(*)} - \lambda_i^{(*)} = 0. \tag{9}$$

Substituting from Eq. (9) into Eq. (7) yields the dual optimization problem:

$$minimize - \frac{1}{2} \sum_{i,j=1}^{n} \left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)\left(y_i . y_j\right) - \varepsilon \sum_{i=1}^{n} \left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{n} y_i \left(\alpha_i - \alpha_i^*\right)$$
$$Subject\ to \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) = 0\ and\ \alpha_i, \alpha_i^* \in [0, C]. \tag{10}$$

In deriving Eq. (10) can be reformulated as $\lambda_i^{(*)} = C - \alpha_i^*$. Equation (9) can be rewritten as follows:

$$w = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\ thusy_i : g(y) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)(y_i . y) + b. \tag{11}$$

The Karush–Kuhn–Tucker (KKT) conditions are the basics for the Lagrangian solution. These conditions state that at the solution point, the product between dual variables and constraints has to be vanished [17, 18].

$$\begin{aligned} &\alpha_i \left(\varepsilon + \zeta_i - t_i + w.y_i + b\right) = 0 \\ &\alpha_i^* \left(\varepsilon + \zeta_i + t_i - w.y_i - b\right) = 0, \end{aligned} \tag{12}$$

$$\begin{aligned} &\left(C - \alpha_i\right)\zeta_i = 0 \\ &\left(C - \alpha_i^*\right)\zeta_i^* = 0. \end{aligned} \tag{13}$$

There are many ways to compute the value of b in Eq. (11). One of such ways can be found in [19]:

$$b = -\frac{1}{2}\left(w.\left(y_r + y_s\right)\right) \tag{14}$$

where y_r and y_s are the support vectors.

2.3 Kernel Trick

The next step is to make the SVM algorithm nonlinear. This, for instance, could be achieved by simply preprocessing the training patterns y_i by a map $\psi : Y \rightarrow F$ into some feature space F, as described in [20], and then applying the standard SVM regression algorithm. Here is a brief look at an example given in [21].

$$minimize - \frac{1}{2} \sum_{i,j=1}^{n} \left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right) K\left(y_i . y_j\right) - \varepsilon \sum_{i=1}^{n} \left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{n} y_i \left(\alpha_i - \alpha_i^*\right), \tag{15}$$

$$Subject\ to \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) = 0\ and\ \alpha_i, \alpha_i^* \in [0, C] \tag{16}$$

Likewise the expansion of g in Eq. (13) may be written as:

$$w = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(y_i)\ thus : g(y) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(y_i . y) + b. \tag{17}$$

An important note here is that in the nonlinear setting, the optimization problem corresponds to finding the flattest function in feature space, not in input space. The details of the conditions for admissible SVM kernel functions can be found in [22]. In this study, we used a radial basis kernel, because this represented choice has a good performance [23, 24].

2.4 Social Spider Optimization

Social spider algorithm (SSA) proposed by James and Li [25] to solve optimization problem. Actually SSO is a swarm intelligence algorithm, according to behavior of the social spiders for optimization tasks. To SSO technique, the following steps need to be performed [10]:

Step 1: Set the total number of n-dimensional colony members as N and define the number of male Nmale and female Nfemale spiders in the entire colony S as given below.

$$\begin{aligned} &N_{male} = N - N_{female} \\ &N_{female} = floor[(0.9 - rand * 0.25)N], \end{aligned} \tag{18}$$

where rand stands for a random number which falls within the range of [0,1] and floor(.) indicates the mapping between a real and an integer numbers.

Step 2: Initialize stochastically the female and male members and compute the mating radius according to Eq. (18).

$$r = \frac{\sum_{j=1}^{n} (p_j^{high} - p_j^{low})}{2n} \tag{19}$$

for (i=1;i<N_f+1;i++)
for (j=1;j<n+1'j++)
$f_{i,j}^0 = p_j^{low} + rand(0,1)(p_j^{high} - p_j^{low})$
end
end
for (k=1;k<N_m+1;k++)
for (j=1;n+1;j++)
$m_{k,j}^0 = p_j^{low} + rand(0,1)(p_j^{high} - p_j^{low})$
end
end

Once the new spider is formed, it is compared to the worst spider of the colony. If the new spider is better, the worst spider is replaced by the new one. Where f_{ij} is the jth parameter of the ith female spider position.

Step 3: Calculate the weight of each spider in colony S through Eq. (19).

$$w_i = \frac{J(S_i) - worst_S}{best_S - worst_S} \tag{20}$$

for (i=1;i<N+1;i++)
calculate w_i
end

where $J(S_i)$ denotes the fitness value acquired through the evaluation of the spider position S_i with regard to the objective function $J(.)$.

Step 4: Move female spiders according to the female cooperative operation modeled as Eq. (20). Since the final movement of attraction or repulsion depends on several random phenomena, the selection is modeled as a stochastic decision. For this operation, a uniform random number r_m is generated within the range [0, 1]. If r_m is smaller than a threshold PF, an attraction movement is generated; otherwise, a repulsion movement is produced.

$$f_i^{k+1} = \begin{cases} f_i^k + \alpha V_i bc_i \left(S_c - f_i^k\right) + \beta V_i bb_i \\ \left(S_b - f_i^k\right) + \delta(rand - 0.5) \\ with\ probability\ PF \\ f_i^k - \alpha V_i bc_i \left(S_c - f_i^k\right) - \beta V_i bb_i \\ \left(S_b - f_i^k\right) + \delta(rand - 0.5) \\ with\ probability\ 1 - PF \end{cases} \tag{21}$$

for (i=1;i<N_f+1;i++)
Calculate $V_i bc_i$ and $V_i bb_i$
if (r_m < PF)
$f_i^{k+1} = f_i^k + \alpha V_i bc_i (S_c - f_i^k) + \beta V_i bb_i (S_b - f_i^k)$
$\delta(rand - 0.5)$
else if
$f_i^{k+1} = f_i^k - \alpha V_i bc_i (S_c - f_i^k) - \beta V_i bb_i (S_b - f_i^k)$
$\delta(rand - 0.5)$
end
end

where α, β and δ and rand are random numbers which fall within the range of [0, 1].

Step 5: Similarly moving male spiders according to the male cooperative operator expressed as Eq. (21).

$$m_i^{k+1} = \begin{cases} m_i^k + \alpha V_i bf_i \left(S_f - m_i^k\right) + \delta(rand - 0.5) \\ \quad if\ W_{N_{female}} + i > W_{N_{female}} + m \\ m_i^k + \alpha \left(\frac{\sum_{h=1}^{N_{male}} m_h^k W_{N_{female}+h}}{\sum_{h=1}^{N_{male}} W_{N_{female}+h}} - m_i^k \right) \\ \quad if\ W_{N_{female}} + i \le W_{N_{female}} + m \end{cases} \tag{22}$$

for (i=1;i<N_m+1;i++)
calculate $V_i bf_i$
if ($W_{N_f} + i > W_{N_f} + m$)
$m_i^{k+1} = m_i^k + \alpha V_i bf_i (S_f - m_i^k) + \delta(rand - 0.5)$
else if
$m_i^{k+1} = m_i^k + \alpha \left(\frac{\sum_{h=1}^{N_{male}} m_h^k W_{N_{female}} + h}{\sum_{h=1}^{N_{male}} W_{N_{female}} + h} - m_i^k \right)$
end
end

where S_f indicates the nearest female spider to the male individual.

Step 6: Perform the mating operation. Mating in a social-spider colony is performed by dominant males and the female members. In the mating process, the weight of each involved spider defines the probability of influence to each individual into the new brood. The spiders holding a heavier weight are more likely to influence the new product, while elements with lighter weight have a lower probability.

Step 7: Check whether the stopping criterion is satisfied. If yes, the algorithm terminates; otherwise, return to Step 3.

Different to other evolutionary algorithms, in SSOA, each individual spider is modelled by taking its gender into account, which allows incorporating computational mechanisms to avoid critical flaws and incorrect exploration exploitation trade-off. In order to show how the SSOA performs [26].

2.5 Results Evaluation

To provide a comparison with the prior prediction ability of SVR models in the "Worldwide Competition within the EUNITE Network", this work evaluated the SSO–SVR model according to the same criteria employed in the above mentioned competition [26].

1. Mean absolute percentage error (MAPE):

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{y_{Ri} - y_{Pi}}{y_{Ri}} \right|}{n} \tag{23}$$

2. Maximum error (ME):

$$ME = Max\left|y_{Ri} - y_{Pi}\right| \tag{24}$$

3. Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{Ri} - y_{Pi})^2}{n}} \tag{25}$$

where y_{Ri} denotes the real value of the test day electrical load and ‘‘i” is hours of day (o till 23) and y_{Pi} represents the predicted test day electrical load of Jun. 1997 in EUNITE Network and n is 24 (Hours a day).

3 Solution Approach

In this paper, a SSO–SVR approach for short term load forecasting is proposed. In this approach, initially SSO is implemented to find optimal SVR parameters (C, ε *and* γ), then SVR with optimal parameters is implemented and obtained 1 week next load, in here has time, climate, calendar days and previous month load as inputs.

The proposed approach is tested on standard data set of EUNITE network (January and February in 1997) of Bratislava city from Slovakia countries. The data sets consists of information of date, working days, holidays and hourly information of time, temperature, humidity, wind speed, wind chill, dew point and load demand.

SSO–SVR is implemented to forecast weekday/weekend load while each day load is predicted for 1 h to 24 h with an interval of 1 h the algorithm of the given approach is as shown with the help of flowchart in Fig. 2. The dataset is composed of two sections. In each case 70% of data is selected as the training system uses initial values for the parameters. These values usually result unacceptable forecasting error rates.

To optimize SVR parameters, the SSO algorithm is applied to the SVR system and will continue running until the MAPE error is below 1.5%.

4 Results and Discusses

In this section proposed approach is tested on EUNITE network (January–February in 1997) to check the performance of suggested approach. For training of SVR in EUNITE network time period from 1st January 1997 to 26 January in 1997 is considered. The remaining data is considered same for testing of SVR in dataset.

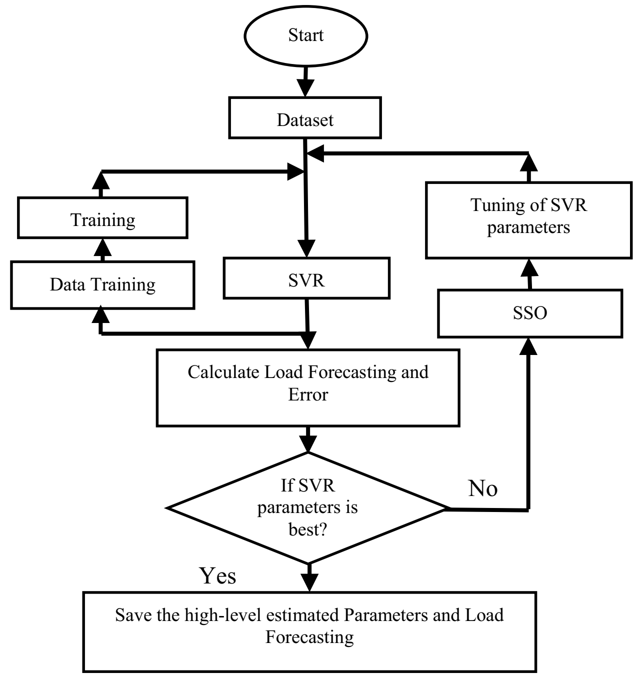

Fig. 2 Flowchart of SSO–SVR

4.1 EUNITE network (January–February in 1997)

The proposed approach is tested on EUNITE network dataset. The relationship between load and temperature, humidity, wind chill and wind speed etc. are as shown in Fig. 3, respectively.

4.2 Training of SVR

As mentioned earlier in Sect. 4 the training of SVR is done for load demand from 1st of January 1997 to 26 of January in 1997 considering various weather condition viz, temperature, humidity, wind chill, dep point, working day, etc.

4.3 Testing of SVR

The trained SVR model after obtain optimize parameters viz SSO is tested for 1 week from 27th January 1997 to 2nd February 1997. The results obtained using SSO–SVR for 1 week (27th January to 2nd February 1997) interval 1 h are shown in Fig. 4 below. On testing the results of 27th January 1997for 24 h for 1 h interval are tabulated in Table 1. The actual load and forecasted load using SSO–SVR are tabulated in 2nd and 3rd column of Table 1, respectively. The Maximum Error, Root Mean Square and Mean Absolute

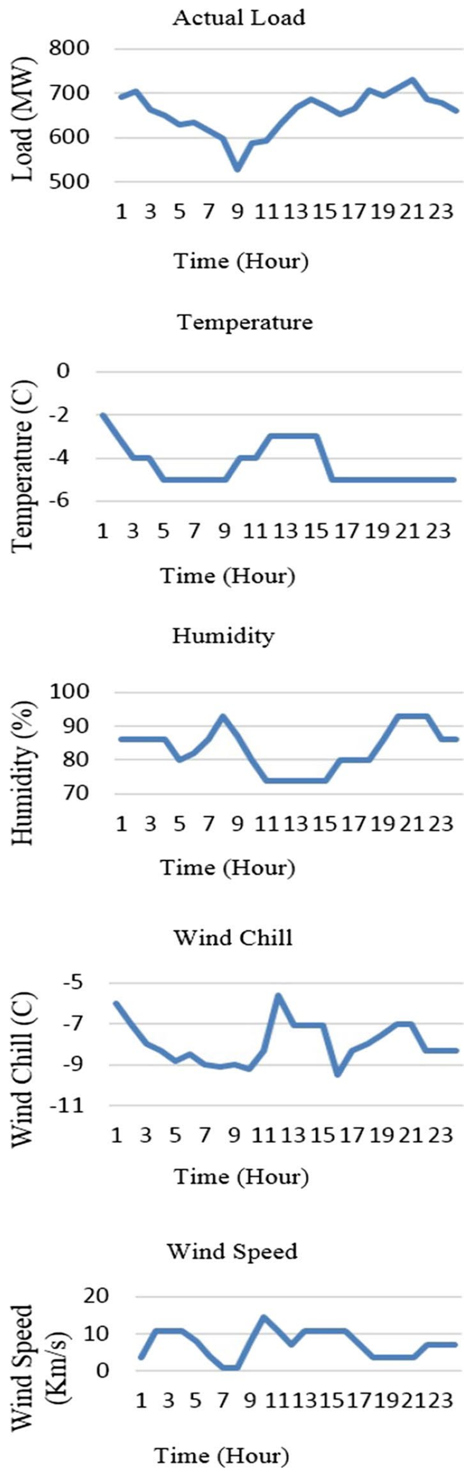

Fig. 3 Relationship between load with temperature, humidity, wind speed and wind chill for EUNITE dataset

Percentage Error for the same are calculated for each hour as shown in 4th, 5th and 6th columns of Table 1. The average MAPE for the given day is 0.014693777.

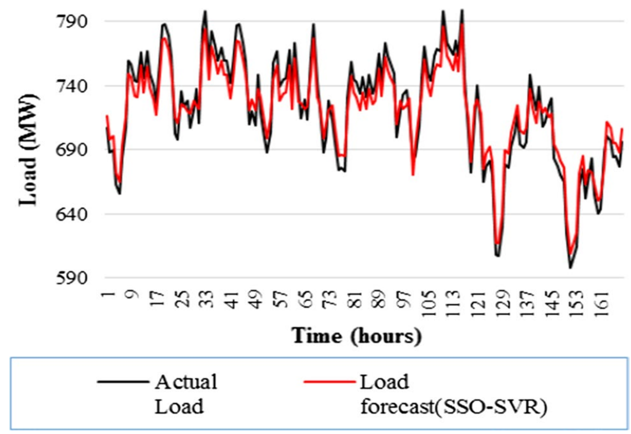

Fig. 4 Predicting load by SSO–SVR for 1 week (27th January to 2th February 1997) in EUNITE

ME, RMSE and MAPE results obtained using SSO–SVR for 1 week aretabulated in Table 2. The effectiveness and applicability of proposed approach is tested by predicting load for 1 week (27th January 1997 to 2nd February 1997), weekdays and weekends also.

The results obtained using SSO–SVR for 1 week interval 1 h are shown in Fig. 4.

Figure 5 shows the comparison between actual load and predicted load for workday (27/01/1997) and weekend (02/02/1997). In this figure MAPE of holiday is more than working day, because SVR system has been more data for training in working days, which results better accuracy.

The MAPE obtained using proposed approach is compared with existing SVR, SVR and Fuzzy, SVR-Firefly, PSO-SVR and ANN + ANFIS based techniques as shown in Table 3.

4.4 Comparison with Other Existing Techniques

It is clear from the above discussion than load forecasting using SSO–SVR has less error as compared to SVR and other existing techniques. It is also clear that the suggested SSO–SVR is suitable for prediction of load under various weather conditions and load conditions for weekdays, weekend and all other calendar days with accuracy.

To check the accuracy of proposed approach, it is implemented on New England Network (2012) dataset. The proposed approach is tested on predicting load for 24 h, a week, weekdays and weekends. As explained in earlier data set, the similar steps are taken for SSO–SVR parameters tuning, training and testing. Table 4 shows the load forecasting for New England network using SSO–SVR for 24 h.

Table 5 shows the comparison of the error rate of different days of the week.

Table 1 Load forecasting for EUNITE network using SSO–SVR for 24 h

Hours	Actual load	Load forecast (SSO–SVR)	ME SSO–SVR	RMSE SSO–SVR	MAPE SSO–SVR
0	707	716.1265	9.1265	9.1265	0.0129
1	688	697.7246	9.7246	9.7246	0.0141
2	690	701.1841	11.1841	11.1841	0.0162
3	663	672.8451	9.8451	9.8451	0.0148
4	656	665.2145	9.2145	9.2145	0.0140
5	683	693.5421	10.5421	10.5421	0.0154
6	707	716.6254	9.6254	9.6254	0.0136
7	760	749.3352	10.6647	10.6647	0.0140
8	757	746.8754	10.1245	10.1245	0.0133
9	744	732.5452	11.4547	11.4547	0.0153
10	743	731.0025	11.9974	11.9974	0.0161
11	766	755.6231	10.3768	10.3768	0.0135
12	746	735.2210	10.7789	10.7789	0.0144
13	767	755.2215	11.7784	11.7784	0.0153
14	750	738.8924	11.1075	11.1075	0.0148
15	740	728.9843	11.0156	11.0156	0.0148
16	727	717.2100	9.7899	9.7899	0.0134
17	761	749.6525	11.3474	11.3474	0.0149
18	787	775.9055	11.0945	11.0945	0.0140
19	788	777.5542	10.4457	10.4457	0.0132
20	779	767.8521	11.1478	11.1478	0.0143
21	763	752.9856	10.0143	10.0143	0.0131
22	703	715.2001	12.2001	12.2001	0.0173
23	698	711.2154	13.2154	13.2154	0.0189
–	–	–	13.2154	10.7860	0.0146

Table 2 Comparison of the error rates in a week

Days	Date	ME SSO–SVR	RMSE SSO–SVR	MAPE SVR
Monday	27/01/1997	13.2154	10.7860	0.0146
Tuesday	28/01/1997	13.7430	11.2856	0.0145
Wednesday	29/01/1997	12.6749	10.9772	0.0147
Thursday	30/01/1997	12.7754	10.8034	0.0146
Friday	31/01/1997	12.1148	11.0497	0.0148
Saturday	01/02/1997	11.9521	10.6736	0.0153
Sunday	02/02/1997	11.7760	10.5417	0.0158
Ave.	–	12.6073	10.8738	0.0149

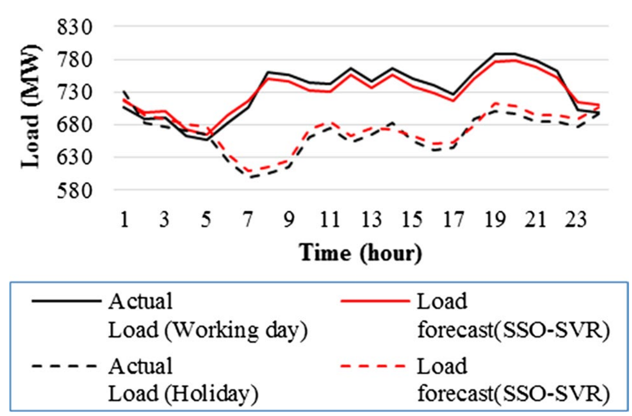

Fig. 5 Comparison between actual load and prediction load for working day and weekend

On comparison it is found that the suggested approach yields minimum error of 0.19326.5.

The relationship between load and temperature, humidity, wind chill and wind speed etc. are as shown in Fig. 6, respectively.

Table 6 shows a 1 week load forecasting for New England network using SSO–SVR in comparison with PSO + SVR [29], ANN + Fuzzy [30] and PSO + SVM [31] methods.

The effectiveness and applicability of proposed approach is tested by predicting load for 1 week (27th January 2012 to 2nd February 2012), week days and weekends also. The results obtained using SSO–SVR for 1 week interval 1 h are shown in Fig. 7.

Table 3 1 week load forecasting for EUNITE network using SSO–SVR

Technique	MAPE (%) EUNITE
ANN + ANFIS [8]	2.796
SVR + Fuzzy [27]	2.13
Firefly + SVR [6]	1.6909
SVR [6, 8]	1.69
PSO-SVR [28]	1.58
SVM + RFR [31]	2.12
Proposed method	1.4693

Figure 8 shows the comparison between actual load and predicted load for work day (27/01/2012) and weekend (02/02/2012) for New England dataset.

Table 5 The comparison of the error rate of different days of the week

Days	Date	ME SSO–SVR	RMSE SSO–SVR	MAPE SSO–SVR
Friday	27.01.2012	0.14295	0.11379	0.0086
Saturday	28.01.2012	0.18491	0.1375	0.01081
Sunday	29.01.2012	0.19326	0.14882	0.01212
Monday	30.01.2012	0.18217	0.14018	0.01002
Tuesday	31.01.2012	0.13546	0.0618	0.00466
Wednesday	01.02.2012	0.10176	0.03829	0.00296
Thursday	02.02.2012	0.10452	0.03881	0.00306
Ave.	–	0.19326	0.09703	0.00746

5 Conclusion

In this paper, a new method of STLF based on SVR and social spider optimization technique (SSO) is presented which has lowest error and highest accuracy. The suggested method has been tested on EUNITE standard network in January and February 1997 and New England standard network in January and February 2012. The load is predicted for a day-ahead with 1-h interval, 1 week, week day and weekend also. The major significance of

Table 4 Load forecasting for New England network using SSO–SVR for 24 h

Hours	Actual load	Load forecast (SSO–SVR)	ME SSO–SVR	RMSE SSO–SVR	MAPE SSO–SVR
0	10.9	11.009562	0.10956	0.10956	0.01005
1	10.5	10.638951	0.13895	0.13895	0.01323
2	10.5	10.638951	0.13895	0.13895	0.01323
3	10.4	10.530261	0.13026	0.13026	0.01253
4	10.4	10.530261	0.13026	0.13026	0.01253
5	11.4	11.520125	0.12013	0.12013	0.01054
6	13.8	13.925642	0.12564	0.12564	0.0091
7	14.8	14.692598	0.1074	0.1074	0.00726
8	15	14.901325	0.09868	0.09868	0.00658
9	15.1	14.978516	0.12148	0.12148	0.00805
10	15.2	15.083261	0.11674	0.11674	0.00768
11	15.2	15.072564	0.12744	0.12744	0.00838
12	15	14.952654	0.04735	0.04735	0.00316
13	14.8	14.688104	0.1119	0.1119	0.00756
14	14.5	14.586251	0.08625	0.08625	0.00595
15	14.6	14.5956926	0.00431	0.00431	0.0003
16	15.3	15.182456	0.11754	0.11754	0.00768
17	16.5	16.380264	0.11974	0.11974	0.00726
18	16.1	15.960254	0.13975	0.13975	0.00868
19	15.6	15.4836241	0.11638	0.11638	0.00746
20	15	14.8854303	0.11457	0.11457	0.00764
21	10.9	11.009562	0.12261	0.12261	0.00863
22	10.5	10.638951	0.14202	0.14202	0.01084
23	10.5	10.638951	0.14295	0.14295	0.01201
–	–	–	0.14295	0.11379	0.0086

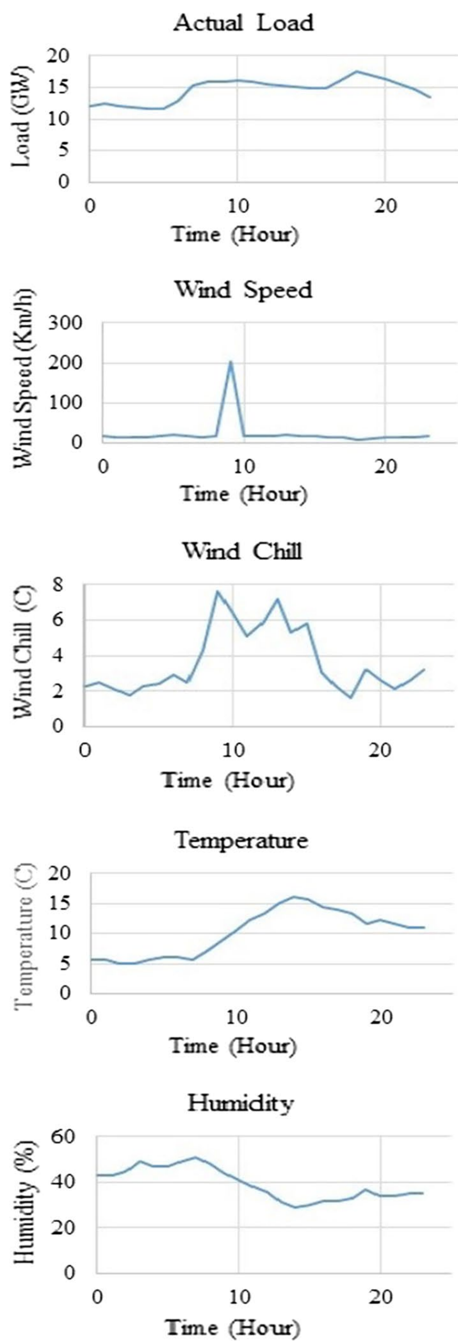

Fig. 6 Relationship between load with temperature, humidity, wind speed and wind chill for New England dataset

this paper is that a new approach to forecast the daily load demand in a short period of time i.e. hourly load demand. The key feature of the proposed approach is the development of SVR approach to solve load forecasting problems. The results for the EUNITE database show that average value of MAPE of 27 Jan. till 2 Feb. 1997 is 1.4954643%. The results for the New England database show that average value of MAPE of 27 Jan. till 2 Feb. 2012 is 0.746%.

Table 6 1 week load forecasting for NEW ENGLAND network using SSO–SVR

Technique	MAPE (%)
PSO + SVR [29]	1.72
ANN + Fuzzy [30]	Weekdays-1.641 Holiday-2.796
PSO + SVM [28]	Working -1.9 Weekend-1.58
Proposed method	Working-0.86 Weekend-1.21

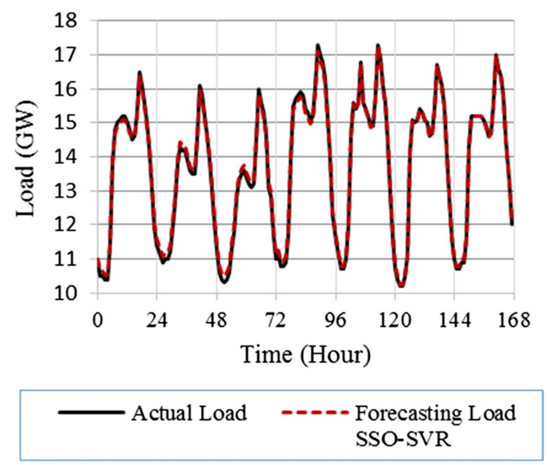

Fig. 7 Predicting load by SSO–SVR for 1 week (27th January to 2th February 2012) in New England

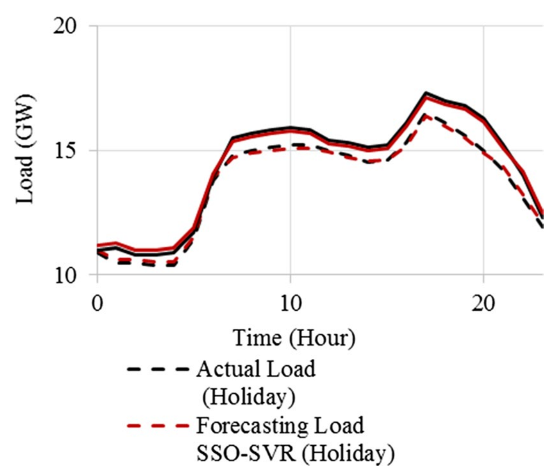

Fig. 8 Comparison between actual load and prediction load for working day and weekend

The comparison between obtained results with other method demonstrates that the proposed approach can decrease error and increase accuracy of STLF.

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