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REVIEW ARTICLE

An Accurate Hybrid Approach for Electric Short-Term Load Forecasting

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ABSTRACT
For efficient working of the power system, an accurate approach for short-term load forecasting (STLF) is suggested. To improve the accuracy of forecasting, various weather conditions, such as temperature, humidity, dew point, wind chill, and wind speed, are considered and their impact on the accuracy of load forecasting is studied in detail in terms of Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Maximum Error (ME) errors. The proposed hybrid approach consists of Support Vector Regression (SVR) and fuzzy because SVR can forecast the ability of small dataset and fuzzy system to handle non-linear weather conditions and uncertainty of load in forecasting. For load forecasting, time of the day, historical load *i.e.* previous one-month hourly load, weather conditions, calendar days for the last 10 days, sunny time, temperature at the same time in previous day, and average temperature of last three hours are taken into account. The proposed approach provides accurate load forecasting for a day regardless of its being a working day or holiday, while fewer days are used for load prediction *viz.* previous one month, while no special care is taken for weekend. The suggested approach is tested on standard electricity datasets: EUNITE network 1997 and New England of America of 2012and 2019. Simulation results show better effectiveness and the superiority of the proposed approach when compared with other existing methods for daily load forecasting *viz.* ANN, Bayesian, and Least Square Support Vector Machine, etc.

KEYWORDS
EUNITE; Fuzzy prediction; Kernel Trick; New England; STLF; SVR

1. INTRODUCTION

The demand for electric energy is continuously increasing, while the sources of energy are depleting day by day. To meet load demand in this constrained environment it became important to forecast it accurately as it affects the performance and operation of the power system in many ways. There are many operations such as unit commitment, economic load dispatch, etc. which are directly influenced by the accuracy of forecasted load [1]. The demand for energy always keeps on changing in a day. Therefore, its accurate forecasting is a complex problem due to changing weather conditions, varying nature of load, and its effect on system performance. Overestimation or underestimation of load forecasting leads to additional spinning reserve, more expansion, or adverse operation of the power system which further cause uneconomical operation and unreliable power system. Therefore, it is important to forecast short-term load forecasting (STLF) in an efficient way for the proper functioning of the power system [2].

In the early 1990s, power system privatization and deregulation came into existence which increased the importance of accurate STLF. As in the deregulated power system, all power utilities are traded in the open market for electricity and its day-ahead pricing [3]. Therefore for the last four decades, researchers are working to devise a suitable technique to forecast load demand.

Authors implemented ANN-based approaches for STLF because of its high speed and quick response [4]. In ANN, weights are updated in such a manner that error is minimized. But later on, it was found that ANN-based approaches face problems of large dataset for training, overfitting, and weight adjustment of connections which is time-consuming. Afterwards, a few researchers implemented an expert system-based method to solve the problem [5,6]. Later on, Fuzzy set-based approaches became common for STLF because of their capabilities to model uncertainties in the data and give accurate results [7–12]. One of the most important problems in forecasting is many inputs.

To overcome the shortcomings of earlier methods and increase the accuracy, authors devised more suitable methods based on the state-space model [13], modified neural network [14–18], wavelet transform [16,19], hybrid [14,20–23], and SVR [24–33]. Some important papers are shown in Table 1 [13–23], while SVR-based methods are discussed in detail [24–33].

Table 1: : Various methods of load forecasting

Ref. No.:	Method	Time horizon
[13]	State-Space models , Ensemble Kalman filter (Enkf), Shrinkage/Multiple Linear Regression	1 interval one week ahead
[14]	Quantile Regression Neural Network using Triangle Kernel Function (QRNNT)	1 interval one week ahead
[15]	Modified Generalized Regression Neural Network (GRNN) Based a Multi-Objective Firefly Algorithm (MOFA)	Half hourly
[16]	Bayesian Neural Network (BNN), L2-Norm, Wavelet Transform.	Half hourly
[17]	Prediction Intervals (Pis), Lower Upper Bound Estimation (LUBE), Neural Network (NN), Particle Swarm Optimization (PSO)	1 interval one week ahead
[18]	Self-Organizing Map (SOM), K-Means Algorithm, Multilayer Perceptron	1 interval one week ahead
[19]	Wavelet Transform, Grey Model, Particle Swarm Optimization	1 interval one week ahead
[20]	Novel Ensemble Method, Wavelet Transform, Extreme Learning Machine (Elm) and Partial Least Squares Regression	1-h and 24-h ahead
[21]	Random Forest (RF), Neural Network (NN) and Fuzzy Inductive Reasoning (FIR)	1 interval one week ahead
[22]	Temporal and Weather Condition Epi-Splines Based Load Model (TWE)	Day-ahead hourly load
[23]	Novel Hybrid Evolutionary Fuzzy Model, Bio-, Inspired Optimizer, So-called GES	1 interval one week ahead

Among these, SVR-based methods are more common because of easiness to comprehend the relationship between input and output variables. SVR requires a small dataset for regression and classifications. SVR overcomes the ANN limitation by introducing SRM (Structural Risk Minimization). But load forecasting is affected by various non-linear factors that influence the accuracy of forecasting. Therefore, authors used large datasets (more than one year) for SVR training and testing and weather conditions as input. SVR has been used widely for one decade for load forecasting [26–33].

The quality of solution of SVR is directly influenced by the input parameters. Therefore, many researchers implemented various techniques for tuning SVR parameters. In this paper, literature survey of the existing techniques using SVR is discussed in detail with respect to input data size and its performance measure in terms of Mean Absolute Percentage Error (MAPE).

In mid-1920s, Genetic Algorithm and simplex optimization were implemented in combination for kernel and parameter selection of SVR to increase the accuracy of forecasting [25]. The proposed approach improves the performance of SVR and yields MAPE of 0.76% for the weekdays only. Authors applied SVR on EUNITE network and New England of America network datasets and SVR parameters are optimized using the social spider optimization technique and obtained day ahead and next week with an interval of 1 h [24]. The MAPE is reduced to 1.495% and 0.746% for EUNITE and New England, respectively.

Afterwards Chiang H W applied an immune algorithm for SVR parameter tuning. They used a large dataset of 20 years for training, validation, and testing [26]. But the accuracy is not so good. It has MAPE of 1.29% while the temperature is taken into account [26]. To include cyclic seasonal change in forecasting authors applied chaotic artificial bee colony in addition to SVR to predict the load of each month, while cyclic seasonal changes of data are taken into account. To forecast load, a large dataset of four and half years is considered for the forecasting model, while MAPE is not improved much *i.e.* more than 2% [27]. Later on, Hu Z. *et al.* applied Memetic algorithm for feature selection and parameter optimization simultaneously of SVR for better accuracy of load forecasting. In this method, previous one-year hourly load data and temperature are selected as input variable for the forecasting model [28]. The approach yields MAPE of 1.09% which is better than the earlier SVR methods.

The selection of kernel function is one of the important factors that affect the accuracy of SVR. Authors considered various kernels *i.e.* simple polynomial, radial basis (RBF), and neural network kernel for classification and regression models [34]. The study reveals that RBF kernel yields smallest error [34]. Keeping this in view, in this study, a radial basis kernel is used because of its good performance [34,35].

Che J. *et al.* used multiple kernels for the learning of SVR and selected the best individual kernel. But still, the proposed approach results in MAPE more than 2% in all kernel functions. While in this approach a small load data are used for SVR training [29].

Later on, authors implemented PSO in addition to SVR for parameter selection [30]. Ceperic E. *et al.* applied PSO for optimizing hyper parameters of SVR, while feature selection algorithm is used to give effective input data which decreased MAPE for 24-hour slightly from 2% to 1.99% while load data of more than two and half years are considered for training one-year data for testing [30].

Selakov A. *et al.* devised a hybrid approach using PSO and Support Vector Machine (SVM) for load forecasting while significant temperature variation is included in the model [31]. For SVM training, 3-year historical load and average temperature are considered. The suggested approach yields MAPE of a small value of 1.85%.

Table 2: Weather conditions inclusion in load forecasting

Reference Nos.:	Time horizon
[13,14,16,19,21,23,24,29,30,34]	Temperature
[13,14,19,21,24,30]	Humidity
[16,19,23,24]	Wind Speed
[30]	Air Pressure
[31,21]	Solar Radiation

Further to reduce MAPE error, authors applied modified Firefly algorithm for parameter tuning of SVR which yields MAPE of 1.6909%; 3-year load data are considered for training and testing [32].

Yang Y. *et al.* suggested an incremental learning model of SVR for better accurate load forecasting for a small data size [33]. In this the dataset for load forecasting is divided into different training sets in such a way that initially a small subset of training set is used for the training of SVR, then an optimal training set is obtained for the given subset which is added to the system. A reconstruction method is used for re-training of SVR for this additional input data. While SVR parameters are selected using nested PSO, the MAPE is reduced to 1.1.8729% for the load forecasting model [33].

For better forecasting of STLF, weather conditions *viz.* temperature, humidity, and wind speed also influence the accuracy significantly. If these factors are ignored, then the most suitable technique cannot give an accurate solution. Therefore, it is important to consider temperature, humidity, dew point, wind chill, wind speed, and calendar days for accurate forecasting of load. Few authors considered these factors as input variables and showed them as in Table 2. It is clear from the literature survey that many authors [13,14,16,19,21,23,24,29,30,34] have taken the temperature variation, while other parameters are ignored.

From the literature survey it is also found that the accuracy of load forecasting for weekend is less as compared to weekdays because of less load data availability for weekend. Few authors forecasted load for weekends, while a special care is given for this [13,16,22].

For better understanding the role of weather conditions, for the last two decades, authors applied artificial intelligence-based approaches to select the most important weather conditions for better accuracy. Z. Hu *et al.* implemented artificial intelligence-based techniques for load forecasting, while proper inputs parameters are selected which increase the accuracy of forecasting and reduce computational burden [36].

O. Abedinia *et al.* proposed a hybrid filter/wrapper feature selection technique for load forecasting. In this Pennsylvania-New Jersey-Maryland (PJM) electricity market data are used and the obtained MAPE for one week are 0.95% [37] and Z. Hu *et al.* used the same method for STLF and implemented North-American electric utility as dataset, and obtained MAPE of 4.52% [36]. Researchers used GA- and PSO-based methods for feature selection [38].

In this work, feature selection is done using genetic algorithm [39] which results in temperature, humidity, and wind speed as more important weather conditions.

Takeda H. *et al.* suggested ensemble Kalman filter and a multiple regression-based method for load forecasting [13].

M. ghofrani *et al.* devised a hybrid approach based on Bayesian neural networks. Authors used a historical load of 5 years for load forecasting. To increase the accuracy of weekend and special days (holidays) sub-series of input set is considered which decreases MAPE for these days to 0.419–1.559% for different sub-series [16].

Feng Y. *et al.* applied temporal and weather conditions epi-spline-based load models. Temperature and dew points are considered, while wind speed is ignored. The proposed approach yields weighted MAPE of more than 2% in all various seasons [22].

It is found that most of the authors modified/split the large input dataset into subsets in order to increase the accuracy of load forecasting for weekends.

Most of the articles written about STLF have tried to improve the forecasting method or choose the right method. But the results show that the accuracy obtained depends on the quality of the data [40]. Y. Yuhang *et al.* proposed a method for feature selection and filtered abnormal data [41]. A. Yang *et al.* suggested a hybrid model that consists of automatic correlation function and least square SVMs in combination for forecasting. The parameters in LSSVM are optimized with Grey Wolf optimization algorithm and Cross Validation [42]. Some sub-series with high correlation and the main load series are selected as features and input to the GRU network, respectively, along with the main load series to select the forecasting model [43].

From the literature survey, the following inferences are drawn:

- It is important to forecast load with a higher accuracy, with small dataset, and with no special efforts for weekend/holidays.
- SVR is a successful tool for load forecasting. SVR performance is directly affected by its parameter tuning.

Keeping the above points in view, in this paper, the following objectives are met.

Initially SVR important parameters, *viz.* C, ε, γ are selected; the SVR model is trained and tested for small datasets, while no special method is used for weekend/holidays.

As SVR is the best tool for load forecasting, this method has considerable accuracy for non-linear data. Because load forecasting depends on non-linear variables such as load, temperature, humidity, and wind speed, etc., these variables are highly non-linear, so the kernel trick is used.

On the other hand, one of the influential factors in the amount of electricity consumption is the issues related to the weather conditions *viz.* temperature felt by people, which is not necessarily equal to the temperature indicated by the thermometer. To convert this qualitative quantity into a numerical quantity, the average temperature of the previous day, and previous three hours has been used together. The best flexible tool that can make flexible decisions is a fuzzy inference system. Therefore, a fuzzy inference system has been used to generate the correction factor. This hourly correction factor is multiplied by the forecasted hourly load value and creates the final forecasted load value. By comparing the error rate, it is found that adding a flexible fuzzy inference system significantly reduces the error.

In this work, temperature, humidity, and wind speed conditions that are taken collectively to increase the accuracy of STLF are considered for load forecasting.

To find the accuracy of forecasting, MAPE, ME, and RMSE errors are calculated which clearly indicates the error in forecasted and actual load. MAPE has been widely used in regression models as a loss function. It has very intuitive interpretation in relative error so it is widely used in the literature [44]. Therefore in this paper, MAPE is used for comparison with other existing methods, while for the proposed approach all three errors *i.e.* MAPE, RMSE, and ME are calculated.

Finally, to check the validity and suitability of the proposed approach, it is tested on two standard datasets: EUNITE network (EUropean Network on Intelligent TEchnologies of 1997 [45] and New England Network of America of years 2012 and 2019 [46]. The results obtained, using the proposed approach, are compared with the existing ANN, Fuzzy, Bayesian probabilistic, and SVR-based techniques. Most research papers used MAPE as an indicator of accuracy of the suggested techniques. But in this paper, MAPE, RMSE, and ME are also calculated for load forecasting for 24 h, weekday, weekend, and one-week forecasting, respectively. Results are compared for datasets using SVR and SVR-F. On comparison of the result, it is found that the suggested approach yields better results for load forecasting and has least MAPE, RMSE, and ME for all cases than SVR and existing methods.

2. PROBLEM FORMULATION

In this section, the basics of SVR and result evaluation criterion are introduced.

2.1 The SVR-based STLF Method

SVM was developed by Cortes and Vapnik in 1995 [44]. SVM became common in various fields due to its ability to solve problems. It has wide applications in classification, regression problems, and load forecasting [26–33] SVM is suitable for a non-linear problem by using a specific transformation function, the kernel function, which maps the data from the original space into a higher dimensional space where as hyperplane separates the data linearly. The optimization procedure adjusts the hyperplane in such a way that the elements of distinct classes are farthest from the separating hyperplane. Retransforming of separating hyperplane into the original n-dimensional space, the typical non-linear, usually non-monotonic SVM-separating function emerges. SVM is suitable not only for classification problem but also for regression problem. Its all main features are retained as in SVM.

This paper presents a novel approach to forecast load for 1-h to 24-h with an interval of 1-h. Climate conditions, small historical load, and calendar date are the input parameters to the SVR system.

2.2 Basic Principles of SVR and Kernel Trick

The regression can be formulated as follows:

SVR works on a regression model. Suppose there is a training dataset D, which has an input vector (x_i), target vector (t_i), and output vectory_i, respectively. y_i is defined in such a way that it has the ability to track these vectors. In practice, vectors may not be tracked correctly in some places, so the Vapnik's loss Function penalty function, represented by $L(t, y)$, is used to correct [24] and is defined as follows:

$$D = \{((x_{i,}t_i),\ y_i)|i = 1,,\ldots,N\} \tag{1}$$

$$L(t,y) = \begin{cases} 0 & \text{if}\,|t-y| \le \varepsilon \\ |t-y| - \varepsilon & \text{otherwise} \end{cases} \tag{2}$$

Function L must be calculated for all data. To do this, the empirical risk function is defined as follows:

$$R_{\text{emp}} = \frac{1}{N}\sum_i L(t_i, y_i) \tag{3}$$

where N is the number of data. The simplest model for the SVR technique is that the data are linear.

$$y_i = w^T \cdot x_i + b \tag{4}$$

where w, b $\in R$.

In the linear model of SVR, R_{emp}, and w^2 are minimized [28,35,47]. 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.

$$L = \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) - t - g - h$$

$$\text{t} = \sum_{i=1}^{n}(\lambda_i\zeta_i + \lambda_i^*\zeta_i^*),$$

$$\text{g} = \sum_{i=1}^{n} \propto_i(\varepsilon + \zeta_i - t_i + (w.y + b))$$

$$\text{h} = \sum_{i=1}^{n} \propto_i^*\ (\varepsilon + \zeta_i^* + t_i + (w.y + b)) \tag{5}$$

where L is the Lagrangian and $\propto_i, \propto_i^*, \lambda_i,$ and λ_i^* are Lagrange multipliers.

In this paper, the data are completely non-linear, so the SVR with Kernel Trick is used [11,25]. An important note here is that in the non-linear setting of the SVR, the optimization problem corresponds to finding the flattest function in feature space, not in input space [34,35].

$$\text{Min} - \frac{1}{2}\sum_{i,j=1}^{n}(\propto_i - \propto_i^*)(\propto_j - \propto_j^*)K(x_i.y_j) - \text{Vare}$$

$$\text{Vare} = \varepsilon\sum_{i=1}^{n}(\propto_i + \propto_i^*) + \sum_{i=1}^{n} y_i(\propto_i - \propto_i^*) \tag{6}$$

2.3 Result Evaluation

To measure the accuracy of STLF, MAPE, ME, and RMSE indicators are used [24]. Among these, MAPE is the most common indicator for accuracy. Therefore, in this paper, the accuracy of results is compared with MAPE.

These are:

(1) Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{\sum_{l=1}^{n}\left|\frac{\text{Actual load}_\text{l}\text{ - forecasted load}_\text{l}}{\text{forecasted load}_\text{l}}\right|}{n} \tag{7}$$

(2) Maximum Error (ME):

$$\text{ME} = \text{Max}|\text{Actual load}_\text{l}\text{ - forecasted load}_\text{l}| \tag{8}$$

(3) Root Mean Square Error(RMSE):

$$\text{RMSE} = \sqrt{\frac{\sum_{l=1}^{n}(\text{Actual load}_\text{l}\text{ - forecasted load}_\text{l})^2}{n}} \tag{9}$$

where l is the hour of day (0 till 23) and n is 24 (Hours in a day).

2.4 Fuzzy Rules for Short-Term Load Forecasting

An accurate load forecasting is a challenge and for the last three decades fuzzy logic-based approaches became common for STLF because of their capabilities to model uncertainties in the data, absorb human experience, and give desired accurate results [7–12,48], as discussed in Section 1.

The structure of fuzzy inference consists of three conceptual components, namely Rule Base containing a selection of fuzzy rules; Database defining the membership functions which are used in the fuzzy rules, and Reasoning mechanism that performs the inference procedure upon the rules and gives facts and reasonable output or conclusion. In this paper, for fuzzy logic 'and' stand for 'min' and 'or' for 'max' [48].

But fuzzy, one of the important issues in load forecasting, has many inputs. This is reduced with the help of SVR.

To utilize fuzzy logic effectively, in this paper, it is used in combination with SVR which can give accurate results with lesser data. After SVR output, fewer number of variables are taken into account in the fuzzy system, as explained in Section 3.3, which improves the accuracy of load forecasting. Therefore in this paper, best advantages of SVR and fuzzy are utilized for the better accuracy of results.

3. SOLUTION APPROACH

In this section, basic steps of the solution approach are discussed. Firstly SVR parameters are selected followed by feature selection for given weather conditions. Afterwards fuzzy rules for load forecasting are discussed and different error calculations are defined.

In this paper, a SVR-Fuzzy approach for STLF is proposed. The proposed approach is tested on three standard datasets of EUNITE network and New England Network in two different years.

3.1 SVR Parameter Selection

Step 1-Read hourly load demand of each day, calendar days, and other climatic conditions for a given dataset.

Step 2-Divide the given dataset into two sets *i.e.* training and testing datasets.

Step 3-During SVR training, select SVR parameters C, ε, γ by varying values for $C = 1:2:100$; $\varepsilon = 0:0.001:3$, and$\gamma = 0:0.005:1$.

Step 4-Evaluate MAPE as given in Equation (7).

Step 5-Select the best SVR parameters corresponding to least MAPE.

Step 6-Test SVR for a day/weekend/weekday/week with obtained values of C, ε, γ as in Step 5 and weather conditions.

3.2 Feature Selection of Weather Parameters

To select the best weather parameters among temperature, humidity, dew point, wind chill, and wind speed, feature selection is done to understand their importance. In feature selection, the aim is to determine the most effective weather conditions. The presence of these reduces the MAPE of SVR.

To select the most vital weather conditions, the steps of feature selection using well-established population-based genetic algorithm is as given below [39]:

Step 1: Initialization

Set the number of chromosome, number of max-iteration, define the features (Temperature, Humidity, Wind Speed, Wind Chill, and Dew Point), set GA operators, and define fitness function.

Step 2: Iteration

Set Iteration $=$ 1 to max-iteration

Set randomly generated chromosome for the selection of feature.

Run SVR and calculate MAPE as in Equation (7).

Step 3: Selection

Store chromosome with best fitness *i.e.* least MAPE.

Select two parents from a population according to their fitness (the better fitness, the bigger chance to be selected).

Step 4: Crossover

Apply a crossover probability to cross over the parents to form new offspring (children).

Step 5: Mutation

Apply a mutation operator to mutate new offspring.

Step 6: Replace

Replace the old offspring with newly generated offspring for the next iterations.

Go to step 2.

In the present work, a population size of 100 is taken, while 1000 iterations are considered. The weather conditions are used as input to the SVR technique. MAPE has been evaluated as a fitness function for a given number of iterations. The feature selection is performed for all three datasets. Finally, the variables that accounted for least MAPE are temperature, humidity, and wind speed. Therefore, in this paper, only these three variables have been used as weather condition variables in STLF. The best solution is achieved in the presence of temperature, humidity, and wind speed as input variables and SVR results in MAPE of 1.1682% and 1.1201 for EUNITE, and New England datasets, respectively. It is clear from the above discussion that temperature, humidity, and

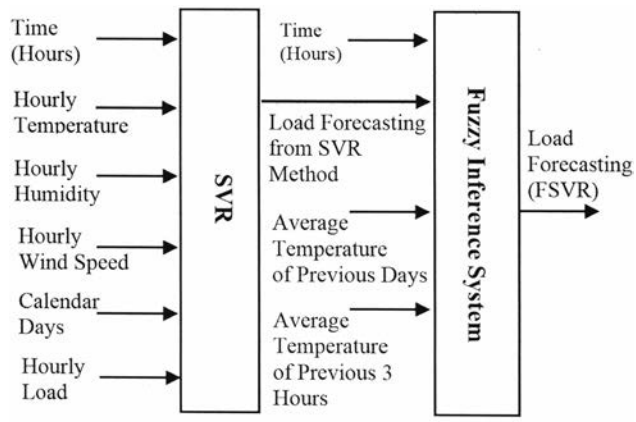

Figure 1: Input parameters of the proposed approach

wind speed are the most important factors that affect the accuracy of STLF.

3.3 Fuzzy Inference System

Step 1: Read Inputs: (Time, forecasted load using SVR, Average Temperature of the previous day, and Average Temperature in previous 3 h).

Step 2: Fuzzification of inputs.

Step 3: Frame fuzzy rules for fuzzy inference system.

Step 4: Defuzzification for load forecasting and MAPE.

In this paper, the inputs to fuzzy inference system consist of forecasted load of SVR, duration of the sunshine in a day (Time), the average temperature in the previous day (Av_Temp), and the average temperature during the last 3 h (Av_Temp_3H), as shown in Figure 1.

To improve the results obtained using SVR, fuzzy rules are framed as given in Table 3 which further improves the quality of the solution. For the fuzzy system, the input variable 'Time' is expressed in linguistic variables using fuzzy set notations such as morning (MO), noon (NO), afternoon (AN), evening (EV), and night (NI). The second and third input variables are 'Av_Temp' and'Av_Temp_3H' of the same day which are expressed in linguistic variables using fuzzy set notations, as mentioned in Table 3. The output variable is 'Gain' and expressed in some linguistic variables using fuzzy set notations such as very decrease (VD), decrease (D), small (S), increase (I), and very increase (VI). The fuzzy rules are interpreted as if 'Time' is MO and 'Av_Temp' is VC and 'Av_Temp_3H' is VC, then the output (Gain) is S. The fuzzy membership functions are shown in Figure 2. The solution approach is presented in a flowchart in Figure 3.

4. RESULTS AND DISCUSSIONS

In this section the proposed approach is tested on EUNITE network (January–February in 1997) and New England Network (January–February in 2012 and 2019). For the training of SVR for EUNITE network time period from 1st January 1997 to 26th January in 1997 is considered, while for New England (2012 and 2019) it is from 1st January to 26th January. The remaining data of EUNITE network and New England (2012 and 2019) Network are considered for testing of SVR-F in both cases. The datasets consist of information of hourly load demand/day, calendar day (working days, semi-weekend, and weekend), hourly temperature, humidity, and wind speed.

4.1 Eunite Network (January–February in 1997)

The proposed approach is tested on EUNITE network 1997 dataset which has the information on load, hourly temperature, humidity, dew point, wind chill, and wind speed.

Initially, for load forecasting, SVR parameters are tuned by changing the values of C, ε, γ from $\{1, 0, 0\}$ to $\{100, 3, 1\}$ with a step size of {2, 0.001, 0.005}, respectively. SVR performance in MAPE is calculated for these variables, as discussed in Section 3.1 which results $C = 48, \varepsilon = 0.005, \gamma = 0.015$ as they have high accuracy and least MAPE error.

Table 3: Fuzzy rules

		Time														
		MO			NO			AN			EV			NI		
		Temp														
		VC	C	N	VC	C	N	VC	C	N	VC	C	N	VC	C	N
Av_Temp_3H	VC	VD	VI	VD	VI	VI	VI	I	S	I	D	I	S	VD	D	S
	C	VD	D	VD	I	VI	I	S	I	I	VD	S	I	S	S	S
	N	VD	VD	D	I	S	D	S	I	I	D	D	I	S	S	S

Note: VC-Very Cool, C-cool, N-Normal, VD-Very decrease, D-Decrease, S-Small, I-Increase, VI-Very increase.

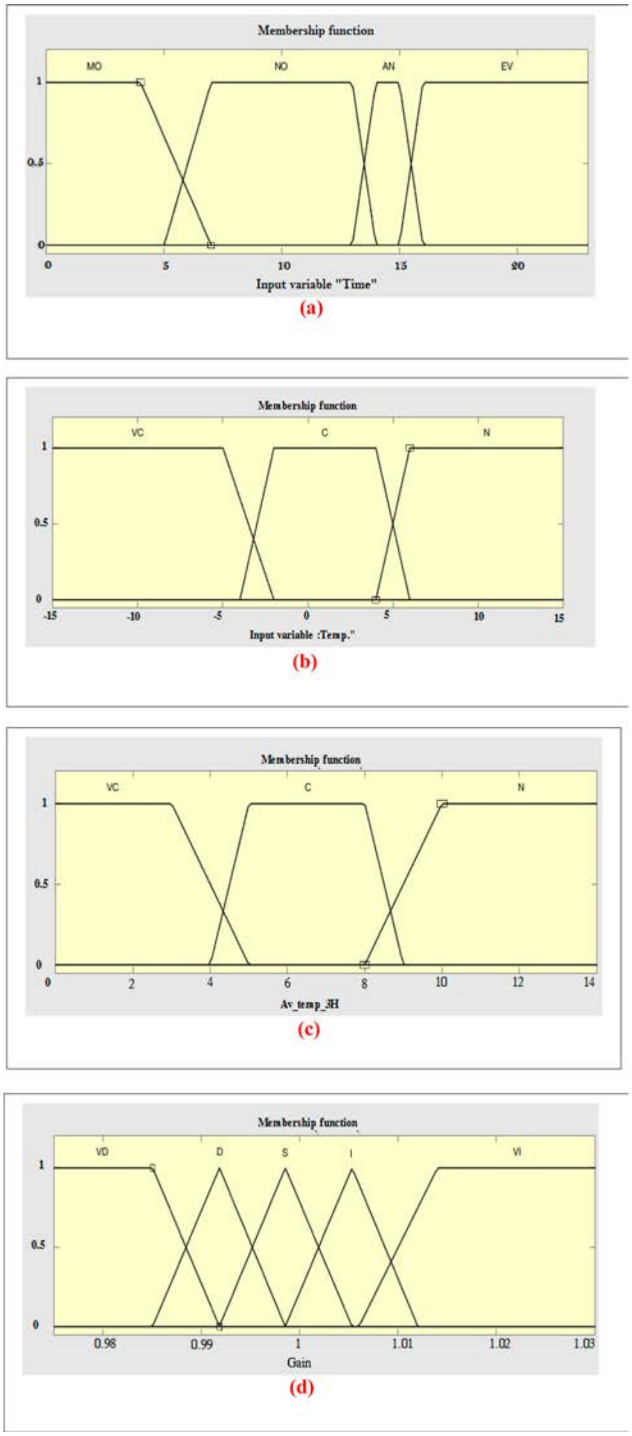

Figure 2: (a) Fuzzy memberships for a day, (b) Fuzzy memberships for the previous day, (c) Fuzzy memberships for the average temperature of 3 h of the same day, and (d) Gain variables of fuzzy members

The training of SVR is done for load demand from 1st January 1997 to 26th January in 1997 considering selected weather conditions *viz.* temperature, humidity, wind chill, and dew point for working and weekend.

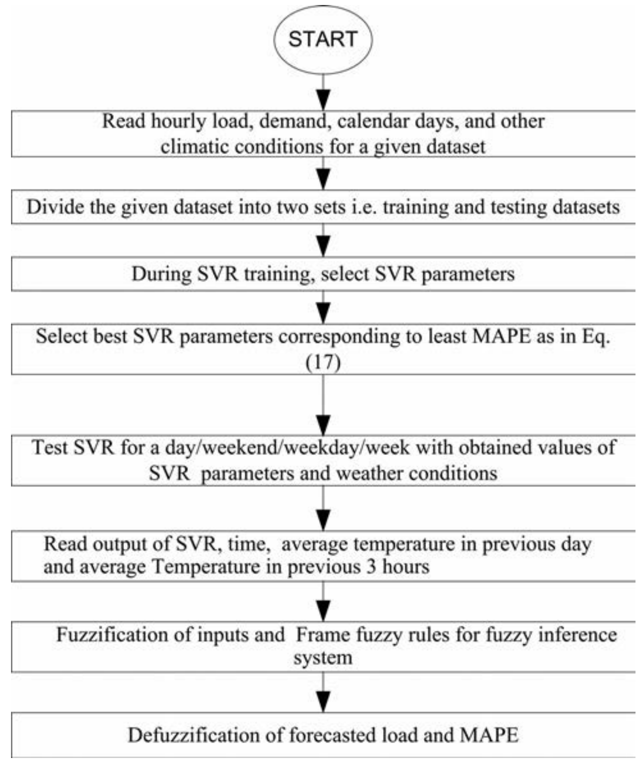

Figure 3: Algorithm of SVR-Fuzzy

The trained SVR model is tested for load forecasting for 24-hour, a week, weekdays, and weekend.

To check the effectiveness of the proposed approach for STLF, it is applied to forecast load for 24-hour with an interval of 1-hour. The results of load forecasting of 27th January 1997 using SVR are shown in the third column of Table 4. This output is given to fuzzy, as discussed in Section 3.3. It is clear from the fourth column of Table 4 that SVR-F forecasts a load which is more close to the actual load. On calculating MAPE it is found that in SVR-F results a small average error of 24 h is 0.27% while in the case of SVR it is 1.17%. While ME and RMSE for the same are 5.18% and 2.41%, respectively, which is again less than SVR as depicted in columns eighth and tenth of Table 4. Comparing the results of SVR and SVR-F, it is found that there is a reduction of ME to 44.60% and RMSE to 71.9% in SVR-F, respectively.

The effectiveness and applicability of the proposed approach are tested by forecasting load for one week (27th January 1997 to 2nd February 1997). The MAPE obtained using SVR and SVR-Fuzzy for one week with an interval of one hour is given in Table 5 and shown in Figure 4. It is clear from Figure 4 that values of real and forecasted load are very near to each other and SVR-F results in a very small error of 0.0079. The Average MAPE

Table 4: Load forecasting for EUNITE network using SVR and SVR-Fuzzy for 24 h

Hour	Actual load	Load forecast (SVR)	Load forecast (FSVR)	MAPE-SVR (%)	MAPE-FSVR (%)	ME-SVR	ME-FSVR	RMSE-SVR	RMSE-FSVR
0	707	715.3828	706.1723	1.19	0.12	8.3828	0.8276	8.3828	0.8276
1	688	696.7553	687.7844	1.27	0.03	8.7553	0.2153	8.7553	0.2153
2	690	698.7161	689.7203	1.26	0.04	8.7161	0.2797	8.7161	0.2797
3	663	672.2455	663.5905	1.39	0.09	9.2455	0.5905	9.2455	0.5905
4	656	665.3828	656.9067	1.43	0.14	9.3828	0.9066	9.3828	0.9066
5	683	691.8534	683.2290	1.30	0.03	8.8534	0.2290	8.8534	0.2290
6	707	715.3828	706.7181	1.19	0.04	8.3828	0.2819	8.3828	0.2819
7	760	751.2455	762.7886	1.15	0.37	8.7545	2.7886	8.7545	2.7886
8	757	748.3043	759.8022	1.15	0.37	8.6957	2.8022	8.6956	2.8022
9	744	735.5592	746.8613	1.13	0.38	8.4408	2.8613	8.4407	2.8613
10	743	734.5788	745.8658	1.13	0.39	8.4211	2.8658	8.4211	2.8658
11	766	757.1279	768.7613	1.16	0.36	8.8721	2.7613	8.8721	2.7613
12	746	737.520	749.2639	1.14	0.44	8.4800	3.2639	8.4800	3.2639
13	767	758.1083	770.1800	1.16	0.41	8.8917	3.1800	8.8917	3.1801
14	750	741.4416	750.9718	1.14	0.13	8.5584	0.9718	8.5584	0.9718
15	740	731.6377	739.9132	1.13	0.01	8.3623	0.0868	8.3623	0.0867
16	727	724.0214	727.8330	0.41	0.11	2.9786	0.8330	2.9786	0.8330
17	761	752.2259	756.1860	1.15	0.63	8.7741	4.8140	8.7741	4.8139
18	787	777.7161	781.8104	1.18	0.66	9.2839	5.1896	9.2839	5.1896
19	788	778.6965	788.4308	1.18	0.05	9.3035	0.4308	9.3035	0.4308
20	779	769.8730	776.5166	1.17	0.32	9.1270	2.4834	9.1270	2.4834
21	763	754.1867	760.6949	1.16	0.30	8.8133	2.3050	8.8133	2.3050
22	703	711.4612	705.6017	1.20	0.37	8.4612	2.6017	8.4612	2.6017
23	698	706.5592	700.7401	1.23	0.39	8.5592	2.7402	8.5592	2.7401
–	**–**	**–**	**–**	**1.17**	**0.27**	**9.3828**	**5.1896**	**8.6042**	**2.4172**

Table 5: Load forecasting for EUNITE network using SVR and SVR-Fuzzy for 24 h

Day	Date	MAPE-SVR (%)	MAPE-FSVR (%)	ME-SVR	ME-FSVR	RMSE-SVR	RMSE-FSVR
Monday	27/01/1997	1.17	0.27	9.3828	5.1896	8.6042	2.4172
Tuesday	28/01/1997	1.02	0.71	7.2679	4.0542	6.4705	2.0418
Wednesday	29/01/1997	1.09	0.83	10.0017	5.8132	8.7108	3.2135
Thursday	30/01/1997	1.11	0.65	7.0035	4.8345	6.1726	1.7846
Friday	31/01/1997	1.16	0.75	9.184	5.7491	8.2341	2.6148
Saturday	01/02/1997	1.16	0.02	11.1080	6.9045	10.0704	5.6081
Sunday	02/02/1997	1.36	1.30	13.1460	7.8413	11.2505	6.1207
Ave.	**—-**	**1.16**	**0.79**	**9.5848**	**5.7695**	**8.5019**	**3.4001**

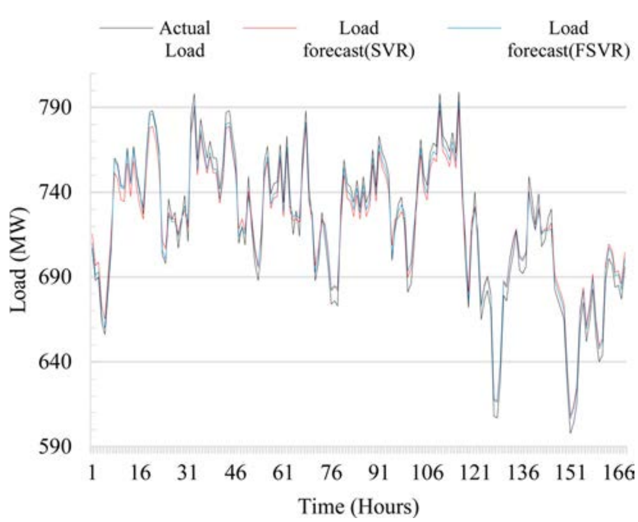

Figure 4: Load prediction using SVR and SVR-F for one week

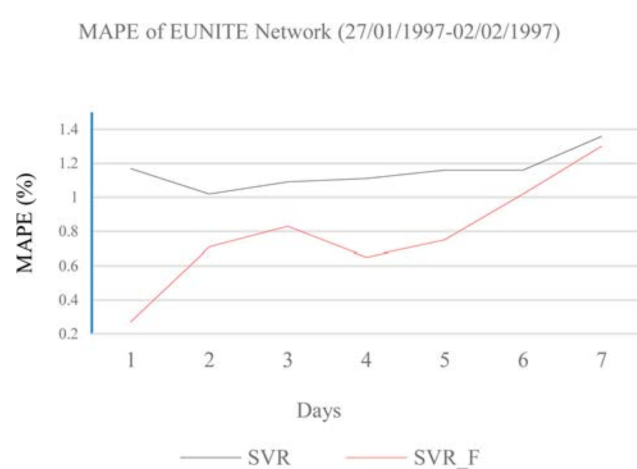

Figure 5: Comparison of MAPE using SVR and SVR-F for a week

for each day of one week is compared using SVR and SVR-Fuzzy is shown in Figure 5. It is clear from Figure 5 that SVR-F results in less MAPE on all day as compared to SVR. This difference is due to the inclusion of fuzzy with SVR which improves the quality of the solution by minimizing the value of MAPE. Similar observations are made for RMSE and ME error using SVR-F.

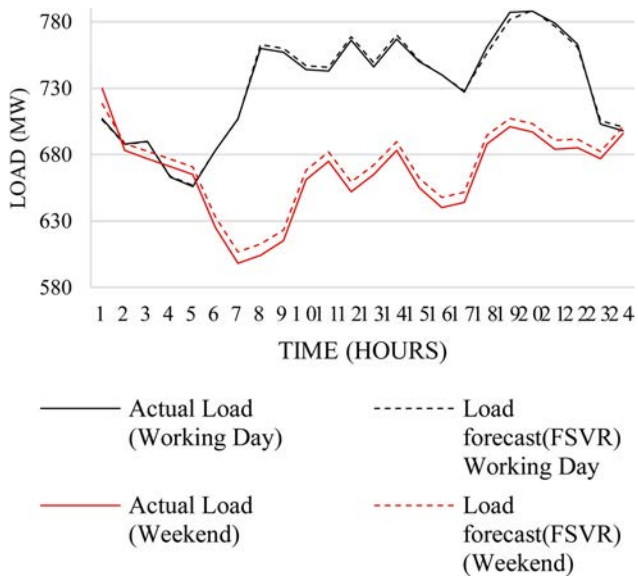

Figure 6: Comparison between actual load and prediction load for workday and weekend.

To check the performance of the suggested approach, results are compared for working day and week day. As in the literature special data creation is done for weekend/holidays. But in the proposed work, no special data manipulation or consideration is taken into account. The results of actual load and forecasted load for working day (27/01/1997) and weekend (02/02/1997) are comparable as shown in Figure 6. It is clear from Figure 6 that in both cases the actual load and forecasted load has a small error *i.e.* in the case of working day it is 0.0027, while 0.01030 for weekend which is comparable.

Hence it is clear from the above discussion that the suggested approach is able to forecast load accurately for all types of cases *i.e.* weekdays, working day, for a small interval of 1 h to 24-hour, and for one week.

4.2 New England (January–February in 2012)

To check the accuracy of the proposed approach, it is implemented on another dataset New England Network 2012. The proposed approach is tested on the forecasting load for 24 h, one week, weekdays, and weekends. As explained for earlier dataset 1st January to 26th January data is taken for the training of SVR and remaining data for testing purposes.

Similar steps are taken for SVR parameter tuning, training, and testing, as mentioned in Section 3.1. Fuzzy rules are framed as given in Section 3.3. For the given dataset values C, ε, γ are taken as in EUNITE network 1997.

After parameter selection, SVR-F is applied to forecast the load for 27th January 2012 for 24 h with an interval 1 h which results in load forecasting, as mentioned in the fourth column of Table 6. On looking at Table 6, it is clear that SVR-F forecasts load in various load conditions more accurately *i.e.* very close to the actual load. It has very small MAPE, ME, and RMSE errors 0.62%, 0.1149, and

Table 6: Load forecasting for New England (2012) network using SVR and SVR-Fuzzy for 24 h.

Hour	Actual load	Load forecast (SVR)	Load forecast (FSVR)	MAPE-SVR (%)	MAPE-FSVR (%)	ME-SVR	ME-FSVR	RMSE-SVR	RMSE-FSVR
0	10.9	11.092465	11.001076	01.76	0.92	0.1925	0.1010	0.1925	0.1010
1	10.5	10.700308	10.612150	01.91	1.06	0.2003	0.1121	0.2003	0.1121
2	10.5	10.700308	10.612150	1.91	1.06	0.2003	0.1121	0.2003	0.1121
3	10.4	10.602268	10.514918	1.94	1.10	0.2023	0.1149	0.2023	0.1149
4	10.4	10.602268	10.514918	1.94	1.10	0.2023	0.1149	0.2023	0.1149
5	11.4	11.582661	11.487233	1.60	0.76	0.1827	0.0872	0.1827	0.0872
6	13.8	13.935602	13.870418	0.98	0.51	0.1356	0.0704	0.1356	0.0704
7	14.8	14.675994	14.903967	0.84	0.70	0.1240	0.1039	0.1240	0.1039
8	15	14.872072	15.102642	0.85	0.68	0.1279	0.1026	0.1279	0.1026
9	15.1	14.970112	15.208522	0.86	0.71	0.1299	0.1085	0.1299	0.1085
10	15.2	15.068151	15.307169	0.87	0.70	0.1318	0.1071	0.1318	0.1071
11	15.2	15.068151	15.304287	0.87	0.68	0.1318	0.1042	0.1318	0.1042
12	15	14.872072	15.103091	0.85	0.68	0.1279	0.1030	0.1279	0.1030
13	14.8	14.675994	14.902461	0.84	0.69	0.1240	0.1024	0.1240	0.1024
14	14.5	14.595693	14.574345	0.66	0.51	0.0956	0.0743	0.0956	0.0743
15	14.6	14.595693	14.574345	0.03	017	0.0043	0.0256	0.0043	0.0256
16	15.3	15.166190	15.246153	0.87	0.35	0.1338	0.0538	0.1338	0.0538
17	16.5	16.342661	16.428824	0.95	0.43	0.1573	0.0711	0.1573	0.0711
18	16.1	15.950504	16.034600	0.93	0.40	0.1494	0.0653	0.1494	0.0653
19	15.6	15.460308	15.541819	0.89	0.37	0.1396	0.0581	0.1396	0.0581
20	15	14.872072	14.950482	0.85	0.33	0.1279	0.0495	0.1279	0.0495
21	14.2	14.327759	14.209709	0.90	0.06	0.1277	0.0097	0.1277	0.0097
22	13.1	13.249327	13.140169	1.14	0.30	0.1493	0.0401	0.1493	0.0401
23	11.9	12.072857	11.973391	1.45	0.61	0.1728	0.0733	0.1728	0.0733
–	–	–	–	**1.11**	**0.62**	**0.2023**	**0.1149**	**0.1506**	**0.0872**

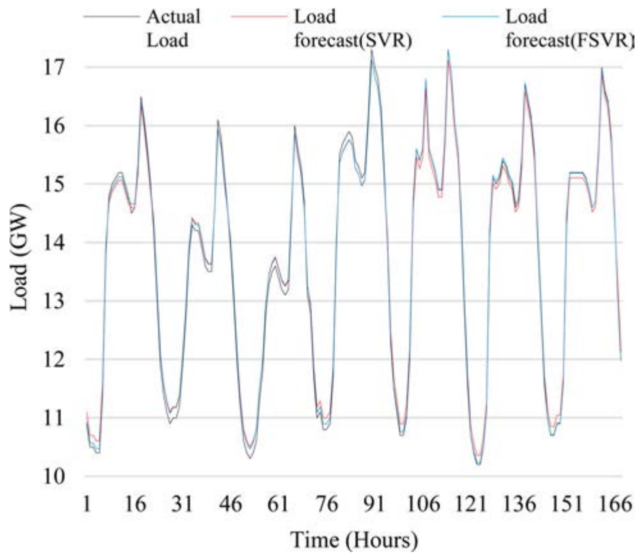

Figure 7: Predicting load by SVR and SVR-F for one week (27th January 2012 to 2nd February 2012)

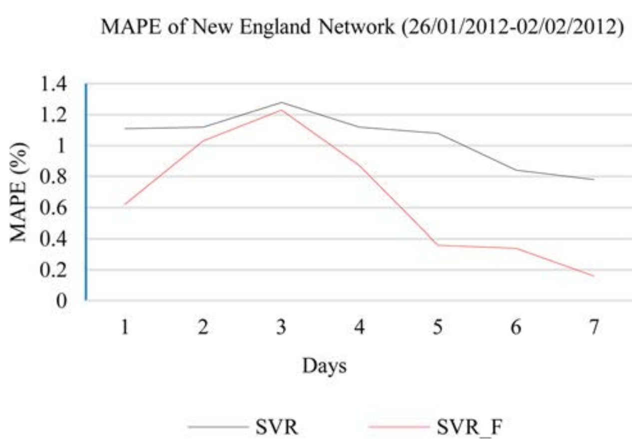

Figure 8: Comparison of MAPE using SVR and SVR-F for a week

0.0872, respectively, which is 44.14%, 43.2%, and 42.09% less than using SVR.

The same hourly approach is extended for load forecasting for one week from 27th January 2012–2nd February 2012. The results are shown in Figure 7 which is approximately the same as the actual load. For one week SVR-F results average MAPE of 0.0066 which is 36.74% less than SVR. On looking at the third and fourth columns of Table 7 the average MAPE, ME, and RMSE per day in SVR-F is less than MAPE per day in SVR for the whole week. Looking at Figure 8, it is found that for all days average MAPE in SVR-F is less than SVR. The maximum MAPE for SVR-F in seven days is 1.23%, while it is 1.28% in SVR.

It is always difficult to forecast load during holidays/weekend because of the small-sized dataset available for these days. The suggested approach proves efficient in

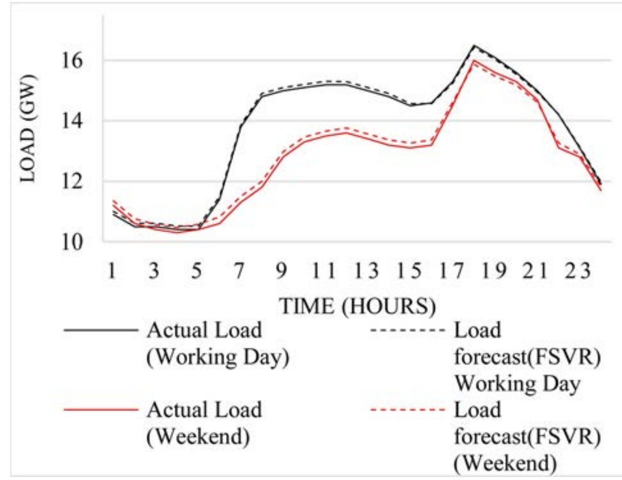

Figure 9: Comparison between actual load and prediction load for workday and weekend

forecasting load for weekend/holidays without any data manipulation. When 24 h load is forecasted on weekend *i.e.* 29/01/2012 it shows a similar pattern as on weekday (27/01/2012) with good accuracy, as shown in Figure 9. These results are obtained even with a small dataset because the suggested approach takes fewer previous day data for load forecasting which makes it suitable to forecast load for weekend with less error *i.e.* 1.23%.

4.3 New England Network (January and February in 2019)

The suggested approach is tested on New England (2019) Network dataset. Like the previous two datasets, the load forecasting is done on an hourly basis and from 1st January to 26th January 2019 as training data and the remaining data are considered for the testing of SVR-F in both cases. The forecasting is done for day-ahead and a week. The SVR parameters are as considered in EUNITE network 1997.

Load forecasting is done for 27th January 2019 for 24 h with an interval of 1 h. The same procedure is carried in two earlier datasets. The obtained results are mentioned in the fourth column of Table 8. On looking at Table 8, it is clear that SVR-F forecast load in various load conditions (weekdays and weekend) more accurately *i.e.* very close to the actual load. It has very small MAPE, ME, and RMSE errors 0.13%, 0.0366, and 0.0203, respectively, which is 44.8%, 50%, and 45.92% less than using SVR.

To check the efficacy of the proposed approach, load forecasting for one week from 27th January 2019 to 2nd February 2019 using SVR and SVR-F is studied. For one week SVR-F results in an average MAPE of 0.19% which

Table 7: Load forecasting for New England week (27th Jan–2nd Feb 2012) using SVR and SVR-Fuzzy

Day	Date	MAPE-SVR (%)	MAPE-FSVR (%)	ME-SVR	ME-FSVR	RMSE-SVR	RMSE-FSVR
Monday	27/01/2012	1.11	0.62	0.1446	0.0819	0.1506	0.0872
Tuesday	28/01/2012	1.12	1.03	0.1617	0.1501	0.1661	0.1529
Wednesday	29/01/2012	1.28	1.23	0.2108	0.1892	0.2231	0.1956
Thursday	30/01/2012	1.12	0.87	0.1586	0.1115	0.1714	0.1185
Friday	31/01/2012	1.08	0.36	0.1371	0.0525	0.1436	0.0594
Saturday	01/02/2012	0.84	0.34	0.1089	0.0481	0.1121	0.0545
Sunday	02/02/2012	0.78	0.16	0.0918	0.0042	0.0961	0.0107
Ave.	–	**1.04**	**0.65**	**0.1447**	**0.0910**	**0.1518**	**0.0969**

Table 8: Load forecasting for New England (2019) network using SVR and SVR-Fuzzy for 24 h.

Hour	Actual load	Load forecast (SVR)	Load forecast (FSVR)	MAPE-SVR (%)	MAPE-FSVR (%)	ME-SVR	ME-FSVR	RMSE-SVR	RMSE-FSVR
0	12.42	12.481317	12.4467	0.49	0.21	0.0613	0.0267	0.0037	0.0007
1	12.35	12.412689	12.3782	0.50	0.22	0.0626	0.0282	0.00393	0.0007
2	12.51	12.569552	12.5347	0.47	0.19	0.0595	0.0247	0.0035	0.0006
3	12.50	12.559748	12.5249	0.47	0.19	0.0597	0.0249	0.0035	0.0006
4	12.76	12.814650	12.7791	0.42	0.14	0.0546	0.0191	0.0029	0.0003
5	13.38	13.422493	13.3852	0.31	0.03	0.0424	0.0052	0.0018	2.7E-05
6	14.86	14.841160	14.8505	0.12	0.06	0.0188	0.0095	0.0003	9.0E-05
7	15.67	15.635278	15.6526	0.22	0.11	0.0347	0.0174	0.0012	0.0003
8	15.71	15.674493	15.6922	0.22	0.11	0.0355	0.0178	0.0012	0.0003
9	15.60	15.566650	15.5833	0.21	0.10	0.0333	0.0167	0.0011	0.0002
10	15.58	15.547042	15.5635	0.21	0.10	0.0329	0.0165	0.0014	0.0002
11	15.45	15.419591	15.4348	0.19	0.09	0.0304	0.0152	0.0009	0.0002
12	15.23	15.203905	15.2169	0.17	0.08	0.0260	0.0131	0.0006	0.0001
13	15.22	15.194101	15.207	0.17	0.08	0.0258	0.013	0.0006	0.0001
14	15.20	15.174493	15.1872	0.16	0.08	0.0255	0.0128	0.0006	0.0001
15	15.21	15.184297	15.1971	0.16	0.08	0.0257	0.0129	0.0006	0.0001
16	15.90	15.860768	15.8803	0.24	0.12	0.0392	0.0197	0.0015	0.0003
17	16.95	16.89018	16.9201	0.35	0.176	0.0598	0.0299	0.0035	0.0008
18	16.48	16.429395	16.4547	0.30	0.15	0.0506	0.0253	0.0025	0.0006
19	15.57	15.537238	15.5536	0.21	0.10	0.0327	0.0164	0.0010	0.0002
20	14.73	14.723177	14.7265	0.04	0.02	0.0068	0.0035	4.6E-05	1.2E-05
21	13.80	13.834258	13.8171	0.24	0.12	0.0342	0.0171	0.0011	0.0002
22	12.56	12.618572	12.5893	0.46	0.23	0.0585	0.0293	0.0032	0.0008
23	11.81	11.88327	11.8466	0.62	0.30	0.0732	0.0366	0.0053	0.0013
–	–	–	–	**0.29**	**0.13**	**0.0732**	**0.0366**	**0.0442**	**0.0203**

is 59% less than SVR. On looking at the third and fourth columns of Table 9 the average MAPE, ME, and RMSE per day in SVR-F is less than MAPE per day in SVR for the whole week. It is found that for all days average MAPE in SVR-F is less than SVR. The maximum MAPE for SVR-F in seven days is 0.25%, while it is 0.42% in SVR.

From the above discussion after implementing the proposed approach on three dataset, it can be concluded that the presented SVR-F always have fewer errors RMSE, ME, and MAPE for weekdays, weekend/holiday and a week. Basically, SVR-F modifies the results of SVR with the fuzzy system which has an output of SVR forecasted load and with a small data of previous 3 h and a previous day. The improvement of results is due to the integration of fuzzy with SVR which is the most widely used tool for regression models.

4.4 Comparison with Other Existing Techniques

The MAPE obtained using the proposed approach (fuzzy-SVR) is compared with the existing SVR [28,30,33], fuzzy [8,12,23], ANN [49–52], Bayesian Probabilistic [53], general regression neural network [54],

Table 9: Load forecasting for New England 2019 using SVR and SVR-Fuzzy for 24 h

Day	Date	MAPE-SVR (%)	MAPE-FSVR (%)	ME-SVR	ME-FSVR	RMSE-SVR	RMSE-FSVR
Monday	27/01/2019	0.42	0.22	0.1319	0.0572	0.0796	0.0367
Tuesday	28/01/2019	0.23	0.22	0.05865	0.0351	0.0665	0.0316
Wednesday	29/01/2019	0.29	0.13	0.0732	0.0366	0.0442	0.0204
Thursday	30/01/2019	0.32	0.25	0.0843	0.0658	0.0928	0.0401
Friday	31/01/2019	0.37	0.19	0.0791	0.0542	0.0712	0.0328
Saturday	01/02/2019	0.29	0.14	0.0884	0.0425	0.0564	0.0254
Sunday	02/02/2019	0.29	0.21	0.1051	0.0626	0.0624	0.0326
Ave.	–	**0.316**	**0.19**	**0.0887**	**0.05057**	**0.06758**	**0.03137**

Table 10: MAPE (%) value of the proposed method and other STLF techniques

Ref.	Weather conditions	Method	Dataset	MAPE (%)
[28]	Temperature	SVR	North American-1988	1.09
[30]	Temperature, Humidity, Air Pressure	SVR	New Enlgand-2006	1.31
[33]	Temperature, Wind Speed	SVR	China	1.18
[12]	Temperature, Wind Speed	Fuzzy	Canada-1994	0.7
[8]	Temperature	Fuzzy Time Series	Malaysia 2010	2.89
[23]	Temperature, Wind Speed	Fuzzy	EirGrid-2014	1.22
[49]	Temperature	ANN	North American-1988	1.68
[51]	Temperature, Humidity, Wind Speed	Gradient Boosting	AEMO-2017	10.8
[50]	Temperature, Dry Bulb, Dew Point	ANN	PJM-2011, New England-2011	2.231.18
[55]	Temperature, Natural Illumination	SVM	Rostov Russia	1.58
[52]	Temperature	DRN	New Enlgand-2006	1.44
[54]	Temperature	GRNN	China	0.81
[53]	Temperature, Dew Point	Bayesian Probabilistic	New Enlgand-2017	2.02
[42]	Temperature, Humidity, Wind Speed	LSSVM	PJM-2015	1.31
			EUNITE -1997	**0.27**
Proposed Method	**Temperature, Humidity, Wind Speed**	**FUZZY-SVR**	**New Enlgand-2012**	**0.62**
			New Enlgand-2019	**0.13**

and SVM, LSSVM-based methods [42,55]. The results of various methods for various datasets in the presence of weather conditions are given in Table 10. It is evident from Table 10 that SVR shows best performance among various existing neural network, LSSVM, and fuzzy-based approaches. While the proposed approach gives better results in all datasets in the presence of temperature, humidity, and wind speed, while a few days of historical data are used as input. The minimum MAPE using SVR as in Ref [28] is 1.09%, while in fuzzy [12] is 0.7%. Other Bayesian probabilistic in the presence of temperature and dew point it has MAPE of 2.02% for New England dataset of the year 2017 [53]. In Ref [42], the same weather conditions are considered as in the present work, linear square SVM results in an error of 1.31% which is more than the suggested approach in all the datasets.

5. CONCLUSION

In this paper, a novel technique is proposed for STLF and tested on two standard networks *i.e.* EUNITE-1997, New England-2012 and 2019. The proposed method includes SVR and fuzzy inference system. To select the best weather parameters among temperature, humidity, dew point, wind chill, and wind speed, feature selection via genetic algorithm is done. Using GA, three variables *i.e.* temperature, humidity, and wind speed are identified as the most influential parameters in STLF and two variables wind chill and dew point are removed from the list of variables related to weather conditions. On applying the suggested approach, MAPE obtained using SVR technique for networks EUNITE-1997, New England-2012 and 2019 for one-week load forecasting with an interval of one hour is 0.316%, 1.04%, and 1.16, respectively. To improve the STLF accuracy, a fuzzy inference system has been added to the SVR technique, causing MAPE to reduce at 0.19%, 0.65%, and 0.79%, respectively. The hybrid fuzzy inference system and SVR technique improved the accuracy of STLF by 39.8%, 37.5%, and 31.9% for 1997, 2012, and 2019, respectively, for standard networks (EUNITE 1997, New England). In general, the proposed method reduces the MAPE error by 0.56% and 1.89% for the standard networks of EUNITE-1997 and New England-2019 as compared to the existing methods.

The suggested approach has more accuracy because of the inclusion of important input weather parameters and fuzzy in addition to SVR. The nonlinearity of weather conditions is successfully handled with a fuzzy inference system. The fuzzy system applies a correction factor by combining input variables such as load value of predicted load using SVR, average temperature information in the previous three hours, as well as the average temperature in the previous day and significantly improves the accuracy of load prediction.

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