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Modeling and Empirical Evaluation of Machine Learning Based Load Forecasting Models for Pakistan

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ABSTRACT

Electric load forecasting (LF) deals with predicting futuristic energy demand of consumers. It is the foremost and important step of energy distribution and generation planning. Machine learning based statistical and artificial intelligence techniques are widely used for LF. Among these, artificial neural networks (ANN) and support vector machines (SVM) emerge as competitive modeling approaches for LF. To further improve the performance of these models, optimization techniques are being used to formulate hybrid LF models. Availability of modern approaches motivated authors to solve the issues with power planning in Pakistan. Hence, we contribute towards proposing machine learning based accurate model of LF on Pakistan power system data set. Several forecasting models are formed using hybrid optimization and model development techniques, which are ranked against their forecasting accuracy and performance. SVM based models performed well and achieved 98.91% accuracy of forecasts. On the other hand, ANN based models showed comparable performance achieving 98.34% accuracy with added ability to avoid over-fitting, and efficiency with improved results.

1. Introduction

Energy generation and distribution planning to meet the current and future needs of consumers is a challenging task. In developing countries, especially in Pakistan generation is not upto the mark. Lack of energy resources, poor planning, and limitation of transmission network are the prominent problems of power sector. Still, to distribute the available energy efficiently, accurate forecasting of energy requirement of customers can contribute a lot. Absence of proper planning and forecasting results in power shortfall and system instability [1]. Electric LF is generally categorized as: short, medium, and long term LF [2]. The short-term LF (STLF) predicts the load demand ranging from one hour to one day [1]. It helps in day to day operation of power systems and in balancing demand and supply curves in real time. Medium-term forecast spans upto several weeks, and it supports decisions related to energy transactions and dispatching, coordination of hydro-thermal generation units, fuel allocation, and scheduling the maintenance plan. Whereas long-term forecast ranges from one year up-to 10 years. These forecasts are used for system expansion, generation and distribution planning, and infrastructure development.

Several LF systems have been developed worldwide and in most cases different countries have adopted different LF systems suitable to their environment conditions. Most of developed models serve the needs of one specific area or country and are customized according to their priorities, custom features and varied input parameters [2].

Beside a number of methods and techniques have been developed and reported in literature but there is a lack of an ample solution that handles all factors, covers all forecast types and is adaptive enough to apply on different geographical locations [1]. Also different models consider varying number of input parameter set based on data availability and impact of these particular inputs on power demand [3]. Therefore, the objectives of this research are to compare and analyze the performance of the learning techniques to formulate ANN and SVM based hybrid models and find the suitable LF model for Pakistan.

The paper structure is as follows: In the next section, there is a brief on LF models and optimization techniques. Section 3, discusses the formulation of STLF model, input data, and modeling techniques. Empirical results on hourly demand data are discussed in section 4. The conclusions of this research work are presented in section 5.

2. Related Work

Electric LF has been a major area of research in the last decade, where more emphasis is laid on recent and more advanced approaches from both statistical and artificial intelligence (AI) domains [1]. Statistical models are

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generally considered rigid in nature and non-responsive to sudden variation in underlying input factors [3]. The time series, regression based methods, radial basis functions (RBF) and support vector regression (SVR) [4,5] fall into statistical category. On the other hand, methods from AI group are: expert systems, ANN and fuzzy logic [6-8].

From the pool of LF models reported in literature, ANN's and SVM's appear as most two popular systems [9,10]. The SVM is a statistical model, evolved from sound theory to experimentation. SVM's have greater generalization ability and are less prone to over-fitting. However, its generalization ability highly dependent on the optimal selection of parameters. Therefore, to obtain better performance of forecasting with SVM; selection of appropriate settings to its parameters is critically important [11]. While, ANN follows a heuristic path of experiment-tation to theory. They have known problems of slow convergence and to stuck in local minima [9]. A lot of effort is reported to overcome the weaknesses of ANN model and to choose appropriate parameters for SVM by use of different optimization methods [12]. These optimization techniques are being used to develop hybrid LF models developed [1]. Since the individual techniques have their own strengths and weaknesses, it becomes difficult to find suitable technique for forecasting. The ensemble models are formulated by combining two or more individual techniques. In this way, overall performance can be enhanced. The hybrid models for LF are widely discussed in literature [2,3]. Whereas, the most recent survey has revealed the potential of ANN and SVM based hybrid models of LF [13]. Several other comparisons of state of the art techniques have emphasized on hybridization of forecasting methods to get more accurate results [14-16].

The optimization techniques used in this experimentation are obtained from different domains, for instance, Levenberg-Marquardt algorithm (LMA) is a statistical learning scheme [17]. LMA is used to overcome the slow convergence of ANN for the estimation of daily peak demand [18]. An average accuracy of 97% was obtained by different models. On the basis of accuracy against different criteria's, LMA based back propagation ANN model is confirmed as best technique for forecasting of daily peak loads [18]. The simulated annealing (SA) is an optimization algorithm derived from metallurgy. The SA finds the global optima by simulating the cooling process and energy states of metal under annealing process [19]. The SA is combined with SVM to solve the electric LF problem [20]. The SVM-SA based model achieved 98.25% of accuracy with better generalization performance compared to autoregressive integrated moving average (ARIMA) and general regression NN (GRNN) models [20]. Adaptive particle swarm optimization (PSO) a computation intelligence algorithm, which is used to find optimal parameters of SVM for LF [21,22]. To keep a balance among exploration and exploitation aspects of swarm; a new scheme for inertia weight adjustment is introduced [22]. This hybrid mode produced an accuracy of 98.32%, where the Back-propagation neural networks (BPNN) and regression models produced 94.93% and 96.42% accurate results, respectively [22]. The resilient back-propagation (RPROP) method performs a direct adaptation of the weight step depending upon the local gradient information [23]. The RPROP trained ANN model shown an average accuracy of 97.40% for 7 days ahead electrical peak LF [23]. Similarly, firefly algorithm (FFA) and artificial bee colony (ABC) algorithm are recently introduced optimization techniques [24, 25]. To overcome premature local optimum and to get better performance in function optimization ABC is employed as learning scheme of SVM for accurate results of LF [26]. This formulation has achieved 97.62% accuracy, better than ARIMA and SA based models. Whereas, FFA is used for parameter optimization of SVM based forecasting model, achieving higher accuracy of forecasts with 98.42% accurate results [27]. Likewise, a recent study has evaluated different optimization algorithms for power demand forecasting in a smart grid environment [28].

3. Materials and Methods

This experimentation is carried out on 6 years (2005-2010) hourly electricity demand data set obtained from National Transmission and Despatch Company Limited (NTDCL) of Pakistan. This is the recording of cumulative load of national grid, thus it represents the consumer demand of whole country, excluding Karachi city of Pakistan. Hourly data contains 24 demand data entries for each day. Consumer demand fluctuates on hourly basis throughout a day. Sample data of one day (January 14, 2010) is shown in Figure 1, where, hourly demand is presented. For STLF, weather is considered as most influencing parameter affecting demand curve fluctuation. As, weather conditions are not same for whole country at the same time, therefore, weather is not considered in this experimentation. Other input parameters include, information of load time and date, holidays, working days or weekends. Usually, there are two peaks and two dips in everyday demand data. On the other hand demand profile of working days is different from off days. As shown in Fig. 1, demand profile of two consecutive days is provided i.e. Sunday and Monday of (15, 16) January 2010. It can be witnessed that peak and off peak loads appear at different hours of the day and demand profile is different for different days. The whole data set is divided into three groups;70% of the data is utilized for training of models, 15% of data is used for testing, while remaining 15% is used for validation of LF models.

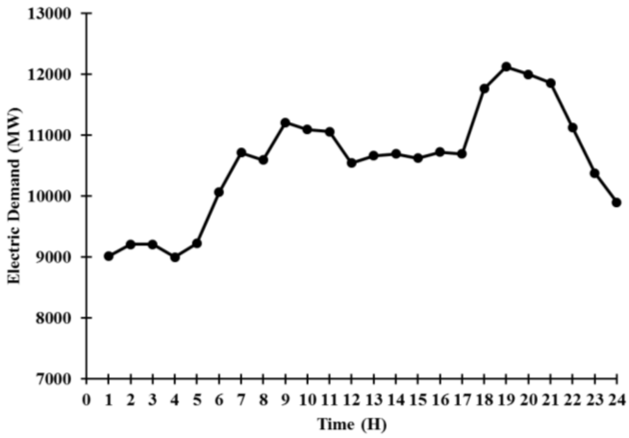

Fig.1. One day demand profile.

3.1 *LF Modeling Techniques*

This experimentation investigates the performance of state of the art models on the Pakistan power systems data set. The ANN and SVM based hybrid models are constructed using 10 different optimization techniques. This makes 20 different LF models with the combination of optimization and modelling techniques; these are listed in Table 1. This experimentation is performed on the Intel based Core i5 machine with 4GB of random access memory (RAM).The LF modeling process is presented via block diagram in Fig. 2.Here inputs (load affecting parameters such as calendar attributes and hourly demands) are passed to LF modelling techniques and objective functions are optimized by learning schemes. Further, the results are evaluated and learning process is terminated upon achieving desired value of objective function. Here, objective function corresponds to error minimization of forecasts. Both, ANN and SVM use their default error minimization equations to evaluate the objective function [9,10]. However, the accuracy of forecasts is measured by taking the mean absolute percentage error (MAPE) [29]. The ANN structure, SVM models and settings of learning algorithms are provided here.

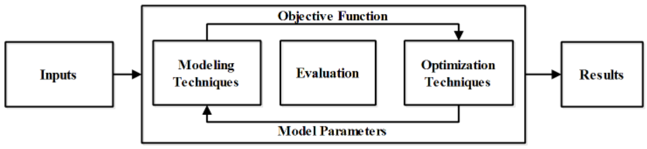

Fig. 2. Components of LF model with learning schemes.

3.1.1 *ANN Model*

In this model, 3 layered feed-forward ANN architecture is used. Input layer corresponds to weighted inputs coming

Table1. Performance comparison of models.

Techniques (10 run)	Train Error	Test Error	Validation Error	Time (Sec)	Iterations	Accuracy (%)
ANN-FFB-FFA	5.63	6.63	5.93	1173	5000	94.17
ANN-FFB-PSO5	2.95	3.26	3.04	257	5000	96.99
ANN-FFB-PSO3	3.81	4.44	4.00	158	3000	96.06
ANN-FFB-PSO10	2.46	2.84	2.57	515	10000	97.46
ANN-FFB-LMA	4.21	2.34	3.64	2006	5000	96.15
ANN-FFB-BACKPROP	7.65	9.05	8.07	58	5000	92.07
ANN-FFB-RPROP	1.55	2.11	1.72	57	5000	98.34
ANN-FFB-SCG	6.39	7.73	6.79	107	5000	93.34
ANN-FFB-ABC	5.99	7.97	6.59	380	5000	93.62
ANN-FFB-SA	2.82	3.43	3.00	1546	5000	97.06
EPSILON-SVR-Search	7.09	7.93	7.34	2	5	92.74
EPSILON-SVR-PSO20	4.71	6.57	5.27	42	20	94.92
EPSILON-SVR-PSO10	4.68	6.58	5.25	24	10	94.95
EPSILON-SVR-PSO5	5.50	6.20	5.71	4	5	94.36
EPSILON-SVR-SA	6.50	7.48	6.79	1	5	93.30
NU-SVR-PSO	2.39	3.49	2.72	166	1	97.39
NU-SVR-PSO5	2.67	4.46	3.21	506	5	96.98
NU-SVR-SA	2.17	3.16	2.47	357	5	97.63
NU-SVR-Search	0.60	3.10	1.35	103	1	98.91
NU-SVR-Search5	2.14	3.14	2.44	494	5	97.66

to network and it consists of 9 neurons; hidden layer contains 6 neurons; whereas, there is a single output neuron in the output layer. Here, sigmoid transfer function is used to get neuron output. We have constituted feed-forward ANN models with one additional bias neuron at each layer. Thus, total weight connections becomes 85 = 10*7+7*2+1. These weights are optimized by utilizing different learning schemes.

3.1.2 SVM Model

In this model two types of SVM based regression models are used, namely Epsilon-SVR and NU-SVR. The RBF kernel is used in this study, its control parameters are tuned by PSO, SA, and default search method of SVM.

3.2 Optimization Techniques

The learning schemes include Back-propagation method; which is the default learning scheme of ANN, scaled conjugate gradient method (SCG), RPROP, LMA, SA, PSO, ABC, FFA and default search method for SVM's. The standard learning parameters for FFA, SCG, and SVM-search method are used in this experimentation. The settings of RPROP, LMA, SA, PSO and ABC are provided here.

3.2.1 RPROP

The RPROP algorithm has two learning parameters, which are: initial update value and step size. Here, initial update value is 0.1 and maximum step size is 50.

3.2.2 LMA

There are two learning parameters of the LMA algorithm; these are: lambda scale and lambda maximum value. The initial value of lambda scale is 10.0, and maximum value is $1e^{25}$.

3.2.3 SA

This algorithm has two control parameters, initial temperature *T1* and stop temperature *T2*. In this study, value of *T1* is 10.0, and *T2* is 0.1; where, *T2*> = 0.

3.2.4 PSO

The settings of PSO algorithm used in this experimentation include the population size *P*, the inertia weight *W*, position and velocity limits *L1 and L2* respectively and two learning rate constants *C1*, *C2*. Here, *P* = 25; *W* = 0.7; *C1* = *C2* = 1.49. The range of both *L1* and *L2* is [-1.0, 1.0].

3.2.5 ABC

In ABC algorithm, the food sources depicts the population count *P*, which is further divided equally as employed and onlooker bees. The dimension of ABC search space *D*, is equivalent to the neuron connection weights, which is 85. Here, P = 28; employed and onlooker bees are 14 each. The upper and lower limits are [-1; 1].

4. Results and Discussion

This research work is carried out on the cumulative hourly demand data of national gridobtained from NTDCL. The results are obtained as average of 10 runs for each hybrid model. The performance comparison of all models is presented in Table 1, time of execution (seconds), number of iterations, training, testing, and validation MAPE, and accuracy of forecasts are presented. Results are categorized into three groups, i.e. ANN based models, Epsilon-SVR models and NU-SVR models. It is evident that Epsilon-SVR models have consumed lesser time, but MAPE is very high. On the other hand, NU-SVR based models taken more time to train, still these have shown better accuracy with lower MAPE. The MAPE is inversely proportional to accuracy of results, higher MAPE corresponds to lower accuracy.

Out of NU-SVR models, NU-SVR-Search method have shown greater accuracy with only 0.60% of train MAPE. But the test MAPE and validation MAPE are higher than train MAPE, resulting in over-fitting of model. From the pool of ANN based models; RPROP with 5000 iterations and PSO with 10000 iterations have shown impressive results. Especially RPROP based ANN-FFB model have produced above 98% accurate results, it is efficient and avoided over-fitting of model. The MAPE comparison is also presented via bar graph in Fig. 3. The accuracy obtained using these models is better than the accuracy of similar approaches reported in literature. We have achieved 98.91% accurate forecasts on NTDCL data sets.

The two days demand profile has been presented in Fig. 4, the actual demand curve is plotted against the curves produced by two best performing models. It can be witnessed that the forecast curves are closely following the actual demand curve of one day in training period. While in forecasting period, the predicted profiles of next day obtained from both models are plotted.

From the results presented in Table 1, we can observe that all of the models have produced more than 92% accurate results on NTDCL data set. ANN-FFB-RPROP and NU-SVR-Search based models appear as competitive approaches in this scenario. Hybrid model of feed-forward ANN with bias and trained with RPROP method emerged as most suitable approach for STLF of this kind.

5. Concluding Remarks and Future Work

In this study, we contributed by evaluating the performance of leading machine learning techniques to propose a best suitable STLF model for the NTDCL. We have compared ANN and SVM based 20 hybrid models, wherein nine different optimization techniques are

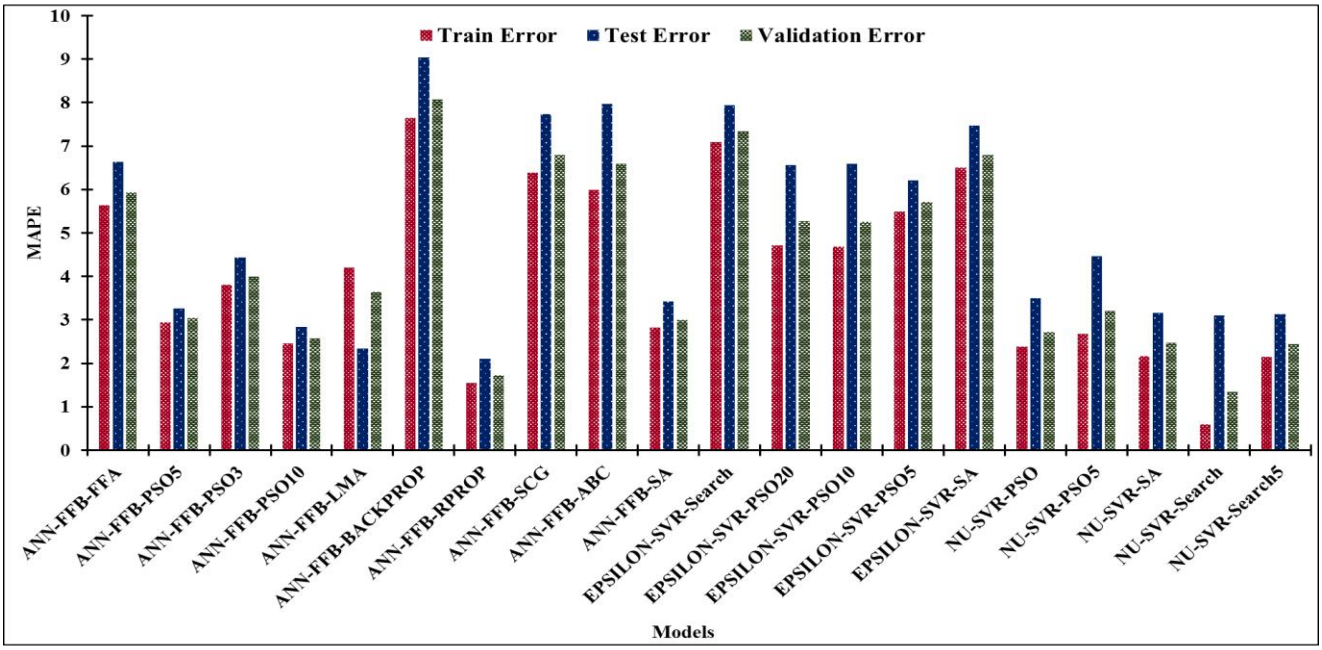

Fig. 3. MAPE Comparison of all models.

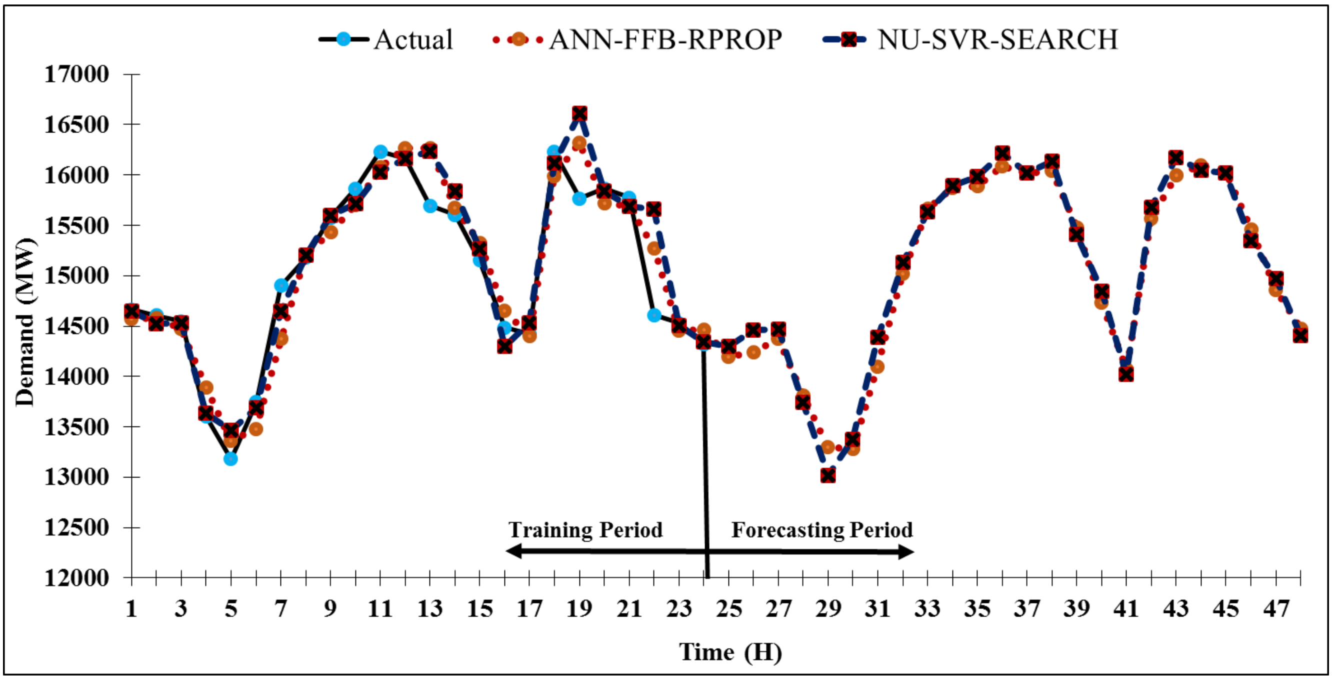

Fig. 4. Twoday profile-actual v/s forecasted.

utilized. From the SVM based models, we have achieved 98.91% accurate forecasts. Whereas, ANN based models have proved more successful to produce comparative accuracy and to avoid over-fitting. The accuracy obtained using these models is greater than accuracy reported in literature and mentioned in related work section. This formulation has satisfied our objectives to produce the accurate results of forecast by using state of the art machine learning model development and optimization techniques. This experimentation was performed on cumulative hourly demand data at national level, collected from NTDCL. The models developed in this research work can be applied to regional power distribution companies to assess the consumer power demand at micro levels. Similarly, we aim at applying these models to forecast medium and long term consumer demands.

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