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Performance Evaluation of Different Optimization Algorithms for Power Demand Forecasting Applications in a Smart Grid Environment

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Abstract

This paper presents an in-depth performance evaluation of three different optimization algorithms, in particular genetic algorithm (GA), particle swarm optimization (PSO), and firefly (FF) algorithm for power demand forecasting in a deregulated electricity market and smart grid environments. In this framework, this paper proposes a hybrid intelligent algorithm for power demand forecasts using the combination of wavelet transform (WT) and fuzzy ARTMAP (FA) network that is optimized by using FF optimization algorithm. The effectiveness and accuracy of the proposed hybrid WT+FF+FA model is trained and tested utilizing the data obtained from ISO-NE electricity market.

Keywords: Electricity market; firefly algorithm; fuzzy ARTMAP; genetic algorithm; load demand forecasting; neural networks; particle swarm optimization, smart grid

1. Introduction

With the emphasis on energy security and sustainability, power utilities are facing a major challenge in maintaining the desired reliability and security of the power supply while integrating new types of loads and generation technologies. Smart grid networks that rely on the exploitation of smart meters enable the design of more accurate forecasting models on the distribution grid. Among various forecasting problems in power system, an accurate and robust load forecasting plays a key role for a reliable and secure operation as well as an economic optimization of the electric energy industry in a competitive electricity market environment. Having reliable load forecast information will help utilities to make important decisions on generating, interchanging, and purchasing electric power, load switching, and infrastructure development. Many operating decisions are based on load forecasting precision, i.e., dispatch scheduling of generating capacity, reliability analysis, and maintenance planning for the generators. Overestimation of electricity load demand will cause a conservative operation, which leads to the start-up of too many units or excessive energy purchase, thereby supplying an unnecessary level of reserve. On the other hand, underestimation may result in a risky operation, with insufficient preparation of spinning reserve,

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causing the system to operate in a vulnerable region to the disturbance [1]. An important feature of smart grid is the intelligent power distribution function based on load forecasting with higher accuracy. The decision-making function of smart grid is based on a large number of collected data. By means of the advanced communications technology, smart grid can obtain the real-time data of each electricity terminal, predict the load and allocate electricity reasonably. The ability of predicting data determines the quality of smart grid. If the predicted value of load is too low, it will lead to allocate low power and power cut. If the predicted value of load is too high, it will lead to unnecessary cost and energy waste. Hence, it is very important to predict load demand accurately.

Several researches have focused on increasing the accuracy of load forecasting techniques in the last few decades. Among thousands of load forecasting literature, some are mentioned in this section. Statistical models that have been used for the short-term load forecasting (STLF) include multiple regression, exponential smoothing, iterative re-weighted least squares, autoregressive moving average (ARMA), kalman filtering, the Box and Jenkins method, spectral expansion technique, and time-series methods are found in several literature [2, 3]. Soft computing models (SCMs) are well known for their capabilities when dealing with non-linear systems and have garnered significant attention in the area of load forecasting. Thus, SCMs, evolutionary programming, and hybrid intelligent algorithm show improved load forecasting accuracy [4]. Among SCMs, the backpropagation neural network (BPNN) is widely used for STLF due to its high forecasting performance [5]. Radial basis function neural network (RBFNN) also shows good STLF performance as it is easy to train, computationally fast, and more general approximator compared to other NNs [6]. Support vector machines (SVMs) are also widely used in load forecasting [7]. In [8, 9], a daily load forecasting model was developed using a chaotic time-series derived from power load demand curves. Furthermore, the combination of NN and fuzzy, such as adaptive neuro-fuzzy inference system (ANFIS) shows significant improved forecasting accuracy. Since ANFIS has a capability of using the expert knowledge of fuzzy system, one can model the complicated relationship between social/environmental factors with the hourly load pattern in an area, which is difficult to find in only NNs [6]. Hybrid methods, such as a combination of RBF and genetic algorithm (GA), wavelet transform (WT) and autoregressive (AR), WT and NNs are also applied for alleviating STLF accuracy [9-11]. Another SCM model based on fuzzy ARTMAP (FA) is a relatively new concept for forecasting applications including load forecasting [14] and wind speed forecasting [15].

This paper presents an application of different optimization algorithms, in particular particle swarm optimization (PSO), GA, and firefly (FF) algorithm for STLF. The major contribution of this paper is to forecast the next 24-hour load demand using the combination of a data filtering technique based on WT and a soft computing model based on FA network that is optimized by using FF optimization algorithm. Comparison of the forecasting performance of the proposed hybrid WT+FF+FA model with that of forecasts obtained from other soft computing (BPNN, RBFNN, ANFIS, and FA) and hybrid (FA+PSO, FA+GA, FA+FF, WT+PSO+FA, and WT+GA+FA) models demonstrate a significant improvement in mean absolute percentage error (MAPE). The test results obtained from the proposed hybrid WT+FF+FA model in all the seasons of the year considering weekdays, weekends and holidays reflect the effectiveness of the proposed hybrid model and demonstrate its superiority over the tested alternatives.

2. Description of the Wavelet Transform, Fuzzy ARTMAP Network and Firefly Algorithm

Detailed description of BPNN, RBFNN, ANFIS, PSO, and GA are available in literature [1, 9-11]. Description of WT, FF, and FA is described below.

2.1. Wavelet Transform

The WT is used to decompose the load demand data into a set of constitutive series. Due to the filtering effect of WT, the constitutive series has better behavior, in terms of data variance and outliers, than original load demand time-series. Therefore, load forecasting will have better error improvement [10]. In WT, low frequencies (large scale) expand the signal and provide non-detailed information regarding the signal, whereas high frequencies (low scales) compress the signal and provide detailed information about the signal. In this paper, three level decompositions have been chosen, consequently three details (D) and one approximate (A) signals are obtained from the original load demand signal. As decomposition involves filtering (high pass and low pass filter) and downsampling, the wavelet reconstruction involves three steps of upsampling and filtering. A wavelet function of type Daubechies of order 4 (db4) is used in this paper as the mother wavelet and was selected based on method similar to [12].

2.2. Fuzzy ARTMAP

The FA network is a supervised learning method based on fuzzy adaptive resonance theory (ART). It is a promising method since FA is able to carry out learning without forgetting previously learned input, it can store previously learned categories (adaptive to changes in the environment) and is self-organizing [13-15]. Most NNs during the learning phase in forecasting application face the plasticity-stability dilemma. The plasticity-stability dilemma asks how a learning system can be designed to remain plastic, or adaptive, in response to significant input data changes, yet also remain stable in response to irrelevant data [14]. Hence, a generic NN has difficulties in preserving previously learned knowledge in memory while continuing to learn new concepts. The FA technique addresses this dilemma by incorporating a feedback mechanism between the competitive and input layers to allow new information to be learned without eliminating previously obtained knowledge. This results in a more stable learning environment and a faster convergence capability [14]. Since load demand time-series is stochastic in nature, this attribute improves load demand forecasting performance. The detailed architecture of the FA network is available in the previous work done by the authors [13].

2.3. Firefly Algorithm

The FF algorithm is a meta-heuristic, nature-inspired, optimization algorithm, which is based on the flashing behavior of fireflies, or lighting bugs. The FF algorithm utilizes three idealized rules based on some of the characteristics of real fireflies [16]: (i) all fireflies are unisex, and they will move towards the more attractive and brighter ones regardless of their gender; (ii) attractiveness is proportional to their brightness, which decreases as the distance from the other firefly increases, and if there is not a brighter or more attractive firefly than a particular one, it will then move randomly; and (iii) the brightness of a firefly is determined by the value of an objective function of a given problem. The FF is a relatively new optimization algorithm and has not been applied in a load forecasting application for optimization purpose. In this paper, the FF algorithm is used to tune the vigilance parameter (ρ) of the FA network.

Data of load demand, price and temperature of past 60 days before the forecast day are used for training the FA network. Since the ρ affects the forecasting performance of the FA network significantly, it is a tedious task to tune its optimized value. Initially during the training phase, authors attempted to obtain the optimized value of ρ based on [17] and the best value of ρ is found to be 0.80. Once the training phase is completed, forecasting error is then calculated. We choose the reciprocal of mean square error as a fitness function for the FA network in the training stage. The fitness function f_i is defined as

$$f_i = \frac{N}{\sum_{i=0}^{N}\left(L_i^{true} - L_i^{forecast}\right)^2} \tag{1}$$

where L_i^{true} is the actual load, $L_i^{forecast}$ is the forecasted load, and N is the total number of data points. The input parameters of FF are the vigilance parameter vector set ρ=[0.1, 0.15, …, 1] and fitness function obtained during the training stage of FA. Thus, the ρ of FA is optimized by FF using the vigilance vector set and the fitness function.

3. Proposed Load Forecasting Procedure Using Hybrid Intelligent Algorithm

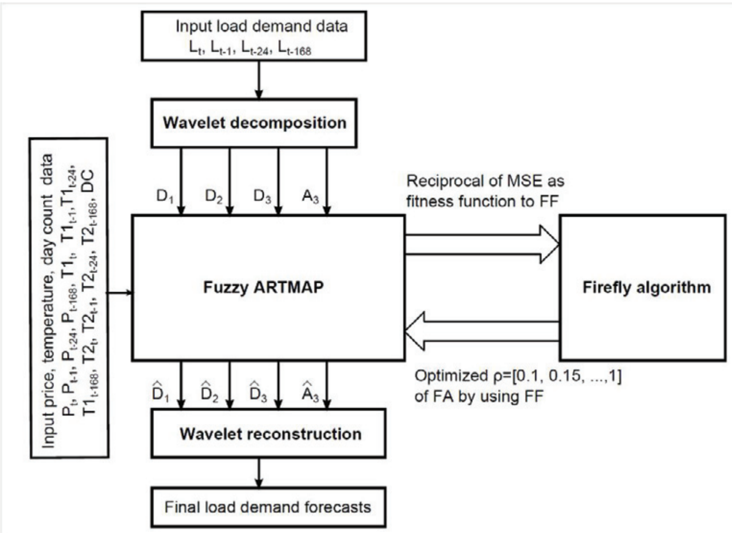
In order to minimize the number of input data, while maximizing the accuracy of the proposed combined approach, authors did analysis to include various time-lag inputs for load, price and temperature into the proposed forecasting model. Finally, the best solution was observed by taking into consideration the effect of load demand (L), electricity price (P), dry bulb temperature (T1), dew point temperature (T2) of current hour (t), previous hour (t-1), previous day (t-24), and previous week (t-168) as inputs to enhance the forecasting capability of the proposed hybrid intelligent model. Load demand patterns in weekdays are different from those in weekends and holidays. Therefore, three different categories of days were classified as day count (DC), i.e., DC=1 for weekday, DC=2 for weekend, and DC=3 for holiday. The schematic diagram for the flow of forecast process is shown in Fig. 1. The forecasting procedure for projecting the next 24-hour load demand is explained below.

Step-1: The load demand (L) data series is decomposed into four components by WT. The decomposed approximation signal (low frequency component, i.e, A_3) and detail coefficients (high frequency components, i.e.,

D_1, D_2, D_3) are obtained by downsampling with low pass filter and high pass filter, respectively. Only the load demand time-series data (L_t, L_{t-1}, L_{t-24}, L_{t-168}) were passed through the WT.

Step-2: In this step, individual decomposed signal from step-1 is fed into the FA network. Other detail coefficient signals follow the similar training procedure. This step-2 also involves the consideration of other input parameters, such as P, T1, T2, and DC into the FA network (see Fig. 1).

Step-3: The individual forecasted value of the decomposed approximation ($\hat{A}_3$) and detail ($\hat{D}_1, \hat{D}_2$, and $\hat{D}_3$) signals will then undergo WT reconstruction process. Finally, the hourly load demand forecasts are obtained.



where
t: current hour at time t
t-1: time at previous hour;
t-24: time at previous day;
t-168: time at previous week;
L: load (MW); P: price ($/MWh);
DC: day count;
T1: dry bulb temperature (Fahrenheit);
T2: dew point temperature (Fahrenheit)

Fig. 1. Schematic diagram of the proposed hybrid WT+FF+FA model for STLF

4. Numerical Results and Discussion

The proposed STLF model based on hybrid WT+FF+FA intelligent algorithm was tested using the data obtained from ISO-New England electricity market. The sampling period is from January to December 2011. MAPE is used as a major criterion to evaluate the forecasting performance of all the models. The MAPE is defined as

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|L_i^{true} - L_i^{forecast}\right|}{L_i^{true}} * 100\% \qquad (2)$$

4.1. Daily Load Forecasting Results

Table 1 presents the next 24-hour load forecasting results obtained from the proposed hybrid WT+FF+FA technique. The results are rigorously compared with other soft computing models, such as BPNN, RBFNN, ANFIS, and FA, and hybrid models, such as FA+PSO, FA+GA, FA+FF, WT+PSO+FA, and WT+GA+FA. Note that two forecasting days (weekday and weekend) are selected from each season. December 12 (Monday) and December 17 (Saturday), October 3 (Monday) and October 22 (Saturday), May 12 (Thursday) and May 22 (Sunday), July 6 (Wednesday) and July 17 (Sunday) of the year 2011 have been chosen from the season – winter, fall, spring, and summer, respectively. The prediction behaviour of the proposed hybrid model for a weekend in fall shows a good performance with a daily MAPE of only 0.92%, which is much lower than the MAPEs obtained from other traditional SCMs BPNN (5.17%), RBFNN (4.91%), and ANFIS (3.99%). It can also be seen in Table 1 that the MAPE for a spring weekday is 4.72% using FA only. When FA is combined with FF, we can see a slight improvement in error, i.e., FA+FF (4.16%), but the result is still not satisfactory. However, a combination of WT, FF and FA resulted into a MAPE of very low value (1.76%). Hence, an inclusion of WT into FF and FA improved the forecasting performance of the proposed model efficiently and it further shows the effectiveness of utilizing WT in this paper. The daily forecasting performance of the proposed model is found to be relatively better in weekend than in weekdays. In general, the weekdays have high load demands compared to the weekends. Note that in all the test cases, the proposed hybrid WT+FF+FA model outperforms the other tested alternatives as presented in Table 1.

The histogram as shown in Fig. 2 presents the comparison of average MAPEs obtained from all the models with the proposed hybrid WT+FF+FA model. The selection of forecasting days has been done randomly. However, similar load forecasting performances have been found for other forecasting days. Due to page limitation, other results are not reported in this paper. In order to further show the prediction capability of the proposed hybrid model, Table 2 presents the results considering the holiday effects. The results obtained from the proposed hybrid model are compared with the other hybrid models, i.e., WT+PSO+FA and WT+GA+FA. As we can see in Table 2, the percentage error improvement due to the proposed WT+FF+FA model over WT+PSO+FA and WT+GA+FA models are in the range of 21-62% and 18-61%, respectively. It is confirmed from Table 2 that the forecasting performance of the proposed WT+FF+FA model is superior to the other hybrid models in all selected holidays, thus showing the superiority of the proposed model even in holidays.

Table 1. MAPE comparison of the proposed hybrid method with other soft computing and hybrid models

Season	**Day**	**Model**									
		BPNN	RBFNN	ANFIS	FA	FA+PSO	FA+GA	FA+FF	WT+PSO+FA	WT+GA+FA	**WT+FF+FA**
Winter	WD	7.15	8.38	7.72	4.58	4.54	4.35	3.72	3.89	3.43	**1.91**
	WE	6.55	7.21	6.29	3.27	3.25	3.14	3.19	2.53	2.56	**1.22**
Spring	WD	6.18	5.74	5.49	4.72	4.68	4.53	4.16	4.11	3.34	**2.07**
	WE	5.76	5.82	5.67	4.83	4.76	4.53	3.98	3.82	2.91	**1.76**
Summer	WD	7.21	6.73	7.06	4.01	3.95	3.77	2.68	3.23	2.76	**1.82**
	WE	6.94	6.83	6.58	3.84	3.80	3.27	2.55	3.04	2.32	**1.92**
Fall	WD	4.92	5.08	4.13	4.88	4.82	4.29	3.36	4.07	3.16	**1.03**
	WE	5.17	4.91	3.99	4.91	4.84	3.78	3.08	3.94	3.10	**0.92**

WD: weekday; WE: weekend; WT+FF+FA: proposed model

Table 2. Load forecasting performance of the proposed model in holidays, USA, 2011

Holidays	**WT+PSO+FA**	**WT+GA+FA**	**WT+FF+FA (proposed)**	**Error improvement over WT+PSO+FA**	**Error improvement over WT+GA+FA**
New Year Day	3.85	4.09	1.56	59.48	61.85
Martin Luther King Day	4.12	3.97	3.22	21.84	18.89
Memorial Day	3.09	2.75	2.04	33.98	25.81
Independence Day	2.64	2.73	1.97	25.37	27.83
Labor Day	2.98	2.80	1.13	62.08	59.64
Columbus Day	5.23	4.88	3.43	34.41	29.71
Veterans Day	4.13	3.91	2.37	42.61	39.38
Christmas Day	3.67	3.72	2.19	40.32	41.12

Load forecasting plays an increasingly important role in electricity market as well as in the smart grid environment due to its impacts on market prices and market participants' bidding strategy. In general, load forecasting is a challenging subject because of the complex features of load and effective data gathering. Proper demand forecasts help the market participants to maximize their profits and/or reduce their possible losses by preparing an appropriate bidding strategy. Traditional intelligent forecasting models need modification to capture the more and more non-linearity in demand signals under the market conditions. In this framework, the proposed hybrid intelligent WT+FF+FA model, as described in this paper, is able to capture the nonlinearity more effectively and improve the forecasting accuracy efficiently. Furthermore, the proposed model is useful for optimizing data quality, strengthening the intelligence on operation and deployment, and it could also be helpful to provide more realistic and workable scientific reference for the decision support of smart grid.

5. Conclusions

In a smart grid environment, the importance of forecasting increases because of the growing challenges and the availability of more data inputs from a data-rich smart grid environment. This paper presented a hybrid intelligent algorithm to forecast hourly load demand considering the examples based on data pertaining to the ISO-New England electricity market. The performances of three different optimization algorithms, such as PSO, GA, and FF were evaluated, and it was found that FF algorithm appeared to be the best among three in order to optimize the FA network for STLF. Combining the WT with FA+FF further enhanced the load forecasting performance. The proposed hybrid WT+FF+FA method was rigorously compared with traditional SCMs, such as BPNN, RBFNN, ANFIS. The test results obtained in weekdays, weekends, and holidays demonstrate a significant improvement in accuracy by the proposed hybrid model over the tested alternatives, thus showing the robustness and efficiency of the proposed method. For future work, we intend to explore an idea of automatic feature selection for our FA model. In addition, we plan to rigorously test our method with multiple smart grid load data sets and fine-tune the method so as to ensure its general usability.

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