Expert Systems with Applications 41 (2014) 6047–6056

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A new hybrid Modified Firefly Algorithm and Support Vector Regression model for accurate Short Term Load Forecasting

Abdollah Kavousi-Fard [a], Haidar Samet [b,*], Fatemeh Marzbani [c]

[a] *Department of Electrical Engineering, Sarvestan Branch, Islamic Azad University, Sarvestan, Iran*
[b] *School of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran*
[c] *American University of Sharjah, Sharjah, United Arab Emirates*

A R T I C L E I N F O

Keywords:
Support Vector Regression (SVR)
Modified Firefly Algorithm (MFA)
Short Term Load Forecasting (STLF)
Adaptive Modification Method

A B S T R A C T

Precise forecast of the electrical load plays a highly significant role in the electricity industry and market. It provides economic operations and effective future plans for the utilities and power system operators. Due to the intermittent and uncertain characteristic of the electrical load, many research studies have been directed to nonlinear prediction methods. In this paper, a hybrid prediction algorithm comprised of Support Vector Regression (SVR) and Modified Firefly Algorithm (MFA) is proposed to provide the short term electrical load forecast. The SVR models utilize the nonlinear mapping feature to deal with nonlinear regressions. However, such models suffer from a methodical algorithm for obtaining the appropriate model parameters. Therefore, in the proposed method the MFA is employed to obtain the SVR parameters accurately and effectively. In order to evaluate the efficiency of the proposed methodology, it is applied to the electrical load demand in Fars, Iran. The obtained results are compared with those obtained from the ARMA model, ANN, SVR-GA, SVR-HBMO, SVR-PSO and SVR-FA. The experimental results affirm that the proposed algorithm outperforms other techniques.

1. Introduction

In order to supply the energy demand constrained on the worldwide limited energy sources, it is essential to provide an accurate electrical load prediction. It is noteworthy that underestimation or overestimation in the electrical load forecast can introduce various challenges to the system operators. Problems in power quality or reliability and insufficient provided reserves stem from the energy demand underestimations. On the other hand, load forecast overestimation results in unnecessary establishments and spinning reserves, inefficient energy distributions, and increasing the operation costs. Therefore, precise load forecast is acquired by utilities and system operators in order to provide efficient unit commitment and load dispatching decisions, contingency planning, and optimal load flow.

Research studies around the accurate load forecast date back to the late 1960s. Based on the prediction horizons, the load forecasting problems can be categorized into three classes: long-term, medium-term, and short-term. Among them, the main focus is on the short-term load prediction which accounts for daily or weekly load estimations (Kavousi-Fard & Akbari-Zadeh, 2014). Moreover, short-term predictors are essential tools for system operation of utilities and electricity markets. There exists a large variety of prediction techniques in short-term forecast subclass. These methods can be divided into two main categories of: classical statistical algorithms and Artificial Intelligence based (AI) methods (Abdel-Aal, 2004; Che-Chiang & Chia-Yon, 2003; Metaxiotis, Kagiannas, Askounis, & Psarras, 2003; Park, El-Sharkawi, Marks, Atlas, & Damborg, 1991; Yalcinoz & Eminoglu, 2005). The statistical techniques include Auto Regressive Moving Average (ARMA) Mbamalu & El-Hawary, 1993, multiple linear regressions, and Kalman filter techniques (Guan, Luh, Michel, & Chi, 2013). The statistical methods identify the load pattern, then based on the obtained pattern, the time series analysis approaches are utilized to provide the future value of the measurements.

Since the early 1990s, the AI techniques are among the most detailed studied forecasting methods. One of the most well-known models in the category of AIs is neural network (NN). In the ANN approaches, in order to obtain the future values, a nonlinear relation is assumed between the previous values and some external variables. Neural fuzzy networks (Li-Chih & Mei-Chiu, 2008; Ling, Leung, & Lam, 2003) and NN variants (Niebur, 1995) have been employed in the last years to provide short term electrical load prediction. The NN models have been extensively used in various applications and they are considered as promising forecasting

* Corresponding author. Tel.: +98 9132131154.
E-mail address: samet@shirazu.ac.ir (H. Samet).

http://dx.doi.org/10.1016/j.eswa.2014.03.053
0957-4174/

tools. Nevertheless, they suffer from a number of weaknesses such as network construction problems, overfitting issue, connection weight estimations, and the need of a large number of data for system training. These problems make it difficult to apply NN methods to some short term prediction problems.

In 1995, an innovative AI technique called Support Vector Machine (SVM) was proposed in order to overcome the shortcomings of the NN methods (Turkay & Demren, 2011). In this method, the Empirical Risk Minimization (ERM) principle is utilized to minimize the training error. Furthermore, SVM employs the structural risk minimization (SRM) principle which is an induction principle minimizing an upper bound of the generalization error. The SRM minimization algorithm is based on the fact that the summation of the empirical errors and a confidence interval term are the boundaries for the generalization error. The objective of the SVMs is to obtain the global optimum and avoid the local optimums. To achieve this task, nonlinear problems are linearly solved in a higher dimension comparing to its original dimensional feature space. The SVM has been employed in wide range of applications such as pattern recognition (Yulan, Reyes, & Lee, 2007), text categorization (Hassan, Muhammad, & Shaikh, 2011; La & Guo, 2012; Oliveira & Sabourin, 2004), and nonlinear regression estimation problems. In the next pace, the SVM model that was first proposed for clustering purposes was expanded to deal with the nonlinear regression problems; shortly called Support Vector Regression (SVR) Vapnik, 1995. The SVR model showed excellent performance in various prediction fields including financial applications (Cao & Tay, 2003; Dianmin, Gao, & Guan, 2004; Sadat Mostafavi, Mostafavi, Jaafari, & Hosseinpour, 2013; Shin, Taik, & Hyun-jung, 2005; Valeriy & Supriya, 2006) and atmospheric science prediction (Yu, Chen, & Chang, 2006) as well as the electrical load prediction (Tian, 2004). As it was expected, the SVR model took successful results in the short time in many areas for instance rainfall forecasting (Hong & Pai, 2007), reliability forecasting (Pai & Hong, 2006), electric load (Hong, 2009), wind speed forecasting (Mohandes, Halawani, Rehman, & Hussain, 2004) and financial problems (Pai & Lin, 2005). The SVR model is characterized by three parameters of C (a parameter to trade off between training error and regression function flatness), δ (kernel function parameter), and ε (constant value to determine the width of the loss function in SVR). The forecast accuracy is highly affected by these parameters. Thus, a major issue with SVR models lies in the proper identification of the above mentioned parameters. Although there have been many research studies suggesting different approaches for setting the SVR parameters, none of them can provide proper effective guide rules.

According to the above discussions, the purpose of this work is to propose a new accurate and robust forecast model for SVR model. The literature has suggested different methods for determining the setting parameters of the SVR (Cherkassky & Ma, 2004). However, there is not yet any accurate and powerful tool available and the study in this area is in its infancy. In addition, most of these methods do not concurrently consider the interaction effects among the three parameters (Hong, 2009). This event resulted in more tendencies for using evolutionary algorithms for adjusting the SVR parameters. In this paper, the setting parameters of the SVR model are adjusted using a new evolutionary based optimization technique called firefly algorithm (FA). In this regard, some of the most well-known algorithms that used by the researchers are particle swarm optimization (PSO) Wu, 2010; Niu & Guo, 2010, Genetic Algorithm (GA) Honga, Dong, Zhang, Chen, & Panigrahi, 2013; Hong, 2009, cuckoo search algorithm (CSA) Kavousi-Fard & Kavousi-Fard, 2013 and chaotic ant swarm optimization (Hong, Lai, Hung, & Dong, 2010). While each of the papers can be assumed as valuable works in the area of adjusting SVR parameters, but they are not as intelligent as FA. Regarding the GA, CSA and ant swarm, these optimization algorithms do not have memory to store the knowledge of the best particle during the optimization process. Therefore, using these algorithms for adjusting the SVR model that is categorized in the class of multimodal optimization problems is prone to bias. On the other hand, PSO algorithm is equipped with the mechanism of memory (both social and personal memory) that makes it a more suitable candidate for finding the SVR parameters. However, it is demonstrated by the inventor of FA that PSO algorithm is a simplified version of FA (especially accelerated PSO algorithm). In addition, FA structure provides the especial aspect of automated subdivision that is a necessity tool for solving multimodal optimization problems. Therefore, FA is more intelligent than PSO algorithm and thus can be more useful for finding the SVR parameters. FA is a stochastic nature-inspired algorithm that mimics the behavior of the firefly animals in the summer of the tropical areas (Yang, 2009). The stochastic characteristic of the FA makes it a suitable candidate for solving complex nonlinear multi-modal optimization algorithms. In comparison with the other well-known optimization algorithms, FA has some especial characteristics such as simple concept, easy implementation, automated subdivision and using the randomization terms in its improvisation stage. In order to find the optimal values of the SVR parameters, having the aspect of automated subdivision helps FA for solving the multi-modal nature of the problem efficiently. In order to improve the performance of FA in the face of different problems, new modifications were developed in recent years that the most well-known are elitist and binary firefly algorithms, Gaussian, Lévy flights, chaos based firefly algorithms, and the parallelized firefly algorithms (Fister, Fister, Yang, & Brest, 2013; Kazemzadeh, 2011). While each of these modifications have provided higher ability for FA, but the dependability of the algorithms on the initial adjusting parameters of FA and possibility of trapping in local optimal yet exit. In addition, none of these modifications are adopted for the case of forecasting through SVR model. Without an appropriate and sufficient knowledge about the SVR model, the optimization algorithm cannot solve the problem properly. Therefore, in order to enhance both the exploration and exploitation abilities of the FA, this work introduces a new modification method based on the crossover and mutation operators as well as an adaptive formulation. The proposed modification method will increase the diversity of the fireflies in the population and thus will reduce the possibility of trapping in local optima when increasing the convergence criterion. We have used the mean absolute percentage error (MAPE) forecast criterion as the fitness function for the proposed modified FA (MFA). In order to demonstrate the feasibility and satisfying performance of the proposed hybrid method, the practical daily load data of Fars province in Iran are used.

2. Support Vector Regression

The SVR model is a novel learning approach firstly used in the pattern recognition problems. It was obtained during 1990s from the statistical learning theory (Hong, 2009). However, later on it was modified and used in the regression problems. The SVR is considered as a thriving algorithm in the learning problems. In the regression problems, training procedure includes obtaining the correlation or nonlinear mapping function $f(x)$ between the input and output of the learner. The SVR aims to provide a nonlinear mapping function to map the training data $\{x_i, y_i;\ i = 1, \ldots, n\}$ to a high dimensional feature space. Then, the nonlinear relationship between the input and the output of the learner can be described by a regression function as follows:

$$f(x) = w^T \varphi(x) + b, \tag{1}$$

where w and b are the coefficients to be adjusted. The empirical risk can be defined as follows: