Applied Energy 217 (2018) 537–549

Contents lists available at ScienceDirect

Applied Energy

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

Integration of new evolutionary approach with artificial neural network for solving short term load forecast problem

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HIGHLIGHTS

- A novel evolutionary based algorithm (FTL) is being proposed.
- FTL is validated by COCO experimental framework on the set of 24 BBOB functions.
- To enhance the accuracy of STLF, we integrate FTL with ANN termed as ANN-FTL.
- Experimental results demonstrate higher prediction accuracy of ANN-FTL.

ARTICLE INFO

Keywords:
Load forecasting
Artificial neural network
COCO framework

ABSTRACT

Due to the explosion in restructuring of power markets within a deregulated economy, competitive power market needs to minimize their required generation reserve gaps. Efficient load forecasting for future demands can minimize the gap which will help in economic power generation, power operations, power construction planning and power distribution. Nowadays, neural networks are widely used for solving load forecasting problem due to its non-linear characteristics. Consequently, neural network is successfully combined with optimization techniques for finding optimal network parameters in order to reduce the forecasting error. In this paper, firstly a novel evolutionary algorithm based on follow the leader concept is developed and thereafter its performance is validated by COmparing Continuous Optimizers experimental framework on the set of 24 Black-Box Optimization Benchmarking functions with 12 state-of-art algorithms in 2-D, 3-D, 5-D, 10-D, and 20-D. The proposed algorithm outperformed all state-of-art algorithms in 20-D and ranked second in other dimensions. Further, the proposed algorithm is integrated with neural network for the proper tuning of network parameters to solve the real world problem of short term load forecasting. Through experiments on three real-world electricity load data sets namely New Pool England, New South Wales and Electric Reliability Council of Texas, we compared our proposed hybrid approach to baseline approaches and demonstrated its effectiveness in terms of predictive accuracy measures.

1. Introduction

Deregulation of electricity industry needs accurate load forecasting for proper electricity load planning and management strategies. Increased complexity and demand of 3–7% electricity load every year require high accuracy of forecasting. An accurate forecast can minimize the gap between electricity supply and demand. To meet the future demand and to decrease energy shortage pressure, some real-time technology innovations are required. In 1985, it was estimated that 1% increase in forecasting error increases the associated operating costs of up to 10 million pounds every year in the thermal British power system [1]. Various new techniques of electricity load forecasting have been proposed in last few decades in order to improve prediction accuracy [2]. Due to the non-linear and random behavior of system loads and weather conditions as well as economic behavior, it is difficult to deal with electricity load forecast problem.

Electricity market has become a central point of interest for researchers in the field of energy sector and load forecast has become one of the most challenging tasks being faced by electricity market entities. The real motivation lying behind load forecasting is purely economic [3]. With the increase in load forecasting accuracy, the negative impact on the economy is reduced. The electricity market players need precise load forecast in order to generate profits and optimize utilities [4].

Generally, four types of load forecaster are used by energy

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https://doi.org/10.1016/j.apenergy.2018.02.131
Received 13 October 2017; Received in revised form 16 February 2018; Accepted 19 February 2018

management systems (EMS) to establish operational planning and their generations in power systems: (1) very short term load forecaster (VSTLF), for generating load demand for few minutes; (2) short term load forecaster (STLF), forecast load demand for one day to one week ahead; (3) forecasting load for more than a week to few months is done by medium term load forecaster (MTLF); (4) long term load forecaster (LTLF) is referred for time horizon between few months to several years. STLF produces an accurate load demand for controlling and scheduling of the power system. Electricity load forecasting models can be broadly classified into four categories: (1) Statistical models; (2) knowledge-based expert systems; (3) hybrid models and (4) artificial intelligence-based models [5].

Statistical models, such as the autoregressive (AR) model, autoregressive moving average (ARMA) model, and autoregressive integrated moving average (ARIMA) model examine qualitative relationships between load and load affecting factors and are easy to implement. Other statistical models such as regression trees [6], and multiple linear regression [7,8] have gained interest among researchers for load forecast. Charytoniuk et al. [9] described a load model in the terms of probability density function of between the load and load factors to solve short term load forecasting problem. Haida and Muto [10] presented a transformation technique based on multivariate regression for daily peak load forecasting by considering seasonal load change, annual load growth and latest daily load change as load affecting factors. El-keib et al. [11] developed a hybrid model by integrating adaptive AR modeling technique with weighted recursive least square estimate algorithm for STLF. Taylor et al. [12] predicted a day ahead load for 10 European countries. The case study compares different univariate models, including ARIMA modeling, periodic AR modeling, Double Seasonal Holt-Winters ES, Intraday Cycle ES Model for Double Seasonality and PCA. However, these statistical models hugely rely on the correlation between the load and its previous load, faces great difficulty in selection of an appropriate non-linear function and suffer from high computational cost [13]. Fortunately, with the rapid advancement in intelligent techniques in last few decades, various soft computing approaches such as fuzzy logic, expert systems, artificial intelligence and many more have been deployed in electricity load forecast problem.

Expert systems are rule-based models that take decisions based on the experience of experts. Ho et al. [14] proposed a knowledge-based expert system for solving STLF of Taiwan power system and proved it to be more effective than Box-Jenkins statistical model. Kandil et al. [15] proposed an expert system that obtains a set of decision rules by relating key variables. Decision rules are stored in the knowledge base, and the best model is used for medium/long term power system planning.

From earlier mentioned limitations of statistical models, researchers started showing their interest towards artificial intelligence, where non-linear relationship from historical data is extracted. Artificial intelligence techniques, such as fuzzy logic system, neural network, evolutionary computation, and support vector machine (SVM), are capable of resolving the non-linear behavior and are highly dynamic to load fluctuation problems. Artificial intelligence models generate slightly better forecast but with longer computation time [16]. Among available intelligence based techniques, artificial neural network has been widely used for solving electric load forecasting problem in last few decades. Mamlook et al. [17] implemented a fuzzy logic controller to decrease the forecasting error on hourly basis. In early 19s, Park et al. [18] proposed neural network for a day ahead hourly load forecast by finding proper correlation among previous, present and future temperatures and loads. Ho et al. [19] proposed a multi-layer neural network with an adaptive learning algorithm to speed up the network training process. The effectiveness of the proposed approach is demonstrated on Taiwan power system for short term load forecasting by showing higher convergence rate than traditional backpropagation learning approach. Chen et al. [20] presented a non-fully connected artificial neural network, capable of forecasting hourly loads for weather sensitive loads. Non-fully connected neural networks have fewer connections which provide the advantage of shorter training time than the fully connected ANN. Taylor et al. [21] analyze the use of weather ensemble predictions in the application of artificial neural networks for load forecasting. Hippert et al. [22] broadly discussed the applications of neural networks and deeply analyzed its performance for short term load forecasting.

In the later stage of research, hybrid methods came into existence by collaborating two or more feasible models to overcome some weaknesses of the original methods. Thus, to find an advanced forecasting method and achieve a higher level of accuracy, hybrid models have emerged. Lately, several hybrid forecasting models have been introduced to improve the load precision with the aim of achieving superior forecasting results. For example, Pai et al. [23] integrated genetic algorithm (GA) with support vector machine (SVM) to find free parameters of SVM for predicting regional electricity load of Taiwan. Liao et al. [24] combined chaos-search genetic algorithm (CGA) with fuzzy system and integrated simulated annealing to find the optimal parameters of fuzzy neural network and applied to short term power system load forecasting. Bashir and El-Hawary [25] combined PSO with artificial neural network (ANN) to find the best network weight solution. Niu et al. [26] implemented ant colony optimization (ACO) for the feature selection of SVM to reduce forecasting error. Li et al. [27], combined generalized regression neural network (GRNN) with fruit fly optimization algorithm (FOA) to find appropriate spread parameters of GRNN for power load forecasting model. Yu and Xu [28] integrated real-coded GA with backpropagation neural network (BPNN) for forecasting short-term gas load and the result shows that improved BPNN obtains higher learning convergence. Quan et al. [5] implemented neural network based method to find prediction intervals by combining PSO integrated with the mutation. Jurado et al. [29] integrated entropy-based feature selection method with soft computing, and machine learning approaches (fuzzy inductive reasoning, random forest, and neural network) for electricity load forecasting. Recently, Khwaja et al. [30] combined two most popular algorithm bagging and boosting with neural network (NN) to improve load forecast of New England Pool region.

Among all available forecasting models, artificial neural network based models have attracted the most for solving STLF problem [22]. Neural network is best known for their learning capability even in a complex non-linear environment. Simplicity of network structure, fault tolerance, and non-linear learning capability of ANN make it widely acceptable. But, the degree of freedom of ANN model reduces with increase in model complexity and it further causes the problem of overfitting or underfitting of the model. For precise forecasting, ANN must have generalization ability for finding the best trend between the load and its affecting factors. On the other hand it requires rigorous network training. The random initialization of weight parameters may generate forecasting error which needs to be updated. To overcome these issues, the network parameters need to be chosen very appropriately. From literature, we observe that hybrid models reduce the magnitude of prediction errors if feasible models are integrated to prevail over some weaknesses of the primitive models. Ling et al. [31] and Azadeh et al. [32] integrated genetic algorithm with artificial neural network (ANN) for selecting appropriate network parameters and compared with traditional neural network and time series models respectively. In similar context, ANN can be combined with other optimization models as a training algorithm in order to achieve optimal neural network weight parameters which may generate least forecasting error. More importantly, accuracy is very significant factor during load forecasting. So, to achieve good forecasting results, limitations of traditional ANN need to be removed by combining with other models.

In this paper, we propose a novel evolutionary algorithm based on the concept of moving behavior of a sheep within a flock. Thereafter,