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Different states of multi-block based forecast engine for price and load prediction

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ABSTRACT

This work proposes different prediction models based on multi-block forecast engine for load and price forecast in electricity market. Due to high correlation of load and price signals, the density of this reaction can affect the demand curve and shift it in market. Furthermore, to improve the operation and planning improvement in the power system, an accurate prediction model can play an important role. So, in this paper, a complex prediction approach is presented based on feature selection, and multi-stage forecast engine. The forecast engine is comprised of multi-block neural network (NN) and optimized by an intelligent algorithm to increase the training mechanism and forecasting abilities. Moreover, different models of multi-block forecast engine are presented in this paper to choose the effective model. In other words, different combinations of NN are tested in the same prediction condition to show their abilities. The proposed model is tested over real-world engineering test cases through comparison with other prediction methods. Obtained results demonstrate the validity of the proposed model.

1. Introduction

1.1. State of art

Nowadays, power grid should be able to handle exploitation of renewable sources, greenhouse gas release decrease, resulted reliability issues and improving the energy production. This form of grid which is called smart grid, has interactions in power market. Moreover, the members of the power market demand stability in market parameters to make the highest possible profit, and this profit is closely related to precise forecast of power cost and demand [1]. The main goal of load/price prediction is providing operation and planning for future electric energy consumption or power load. Also, this problem is very important for power systems planning, power market operation, power market design, power systems control and security of supply. In other words, by accurate forecasting, 1% Reduction of Mean Absolute Percentage Error (MAPE) is impressive in power system to get the range of 3–5% which can decrease the generation costs about 0.1% to 0.3% [1]. For this purpose, various models are suggested for forecasting the power market recently. Though, sufficiently precise prediction has not been achieved so far [2–3].

1.2. Literature review

The autoregressive integrated moving average (ARIMA) and neural network (NN) are introduced in [4] for the purpose of prediction of cost and demand inputs. Also in [5], the generalized autoregressive conditional heteroscedasticity (GARCH) is proposed. The artificial neural network (ANN) is implemented on price prediction in [6]. The mixture of improved ARIMA procedure and wavelet transform (WT) is proposed in [7]. Refs. [8,9] have proposed hidden Markov model and fuzzy inferred neural network, respectively.

The mixture of ARIMA procedure and wavelet transform using the power market prediction is proposed in [10]. In this contribution, in order to get the prediction outcomes, they have utilized the wavelet transform procedure to separate the historical data, utilized the ARIMA

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and finally, employed the inverse wavelet transform. The ANN is implemented for price forecast by utilizing the history and approximated future parameters to deduce the price and quantities in [11]. This contribution proposes the three layer back propagation (BP) neural network (NN) using the demand and fuel cost in the market as entry data. Ref. [12] has mixed the probability neural network (PrNN) and orthogonal experimental design (OED) for forecasting the power price. In this paper, they have employed the probability neural network for classification and orthogonal experimental design for locating the best variable that can lead to higher forecast precision. Ref. [13] has proposed the support vector machine (SVM) for prediction of price based on the price and load history as well as projected assessment of system adequacy (PASA) as the entry data. In this contribution, they have conducted their assessment by making use of Australian national electricity market (ANEM) and regional data of south wales. The time series forecast procedure using the fish swarm algorithm (FSA) is implemented to elect the SVM variables in [14]. This combinatorial procedure uses the power price for data entry. The mixture of wavelet packet transform (WPT) and feature selection is presented in [15]. This paper has proposed the least square support vector machine (LSSVM) for prediction. In Ref. [16] a probabilistic power price prediction method consisting active training procedure and variational heteroscedastic Gaussian process is proposed. Moreover, Ref. [17] has suggested the combinatorial procedure using the SVR and ARIMA. The mixture of WT, radial basis function neural network (RBFNN) and ARIMA is proposed in prediction of price in [18]. In [19], the authors proposed a mixed model for load and price prediction based on interactions of these two prediction processes. The model consists of an iterative neural network based prediction technique. In [20], the authors presents a model for price-directed demand response steered by market signals and expectation method. In this work, Virtual Budget approach is developed couples price and load prediction, and lets automated morphing of a consumers electricity demand. The authors in [21], proposed a new hybrid mode for prediction of load and price. In this work, a hybrid time-series and adaptive wavelet neural network (AWNN) model is applied, in which multivariate autoregressive integrated moving average catches the linear relationship of input signal, generalised autoregressive conditional heteroscedastic unveils heteroscedastic character of residuals and adaptive wavelet neural network presents non-linear impacts. More price and demand forecasting methods are proposed in Refs. [22,23] for further studies.

Due to the mentioned forecasting review, an accurate prediction model is still demanded. In the mentioned models, the researchers didn't compare their works in different modes. Regarding our previous work in [23], we found high accuracy of multi-block forecast engine based on cascade model. In [23], we checked the optimal number of blocks in series model and other models of forecast engine didn't check. Accordingly, in this paper we will check different models of forecast engine based on multi-block and evaluate the prediction accuracy in each of them to find the best solution. In other words, combination of proposed methods should be based on finding the best mode and appropriate syntax.

On the other hand, different feature selection algorithms have been proposed by researchers to find the minimum subset of the primary candidates, through preserving the main information passed by the original set, to create simple and easy future analysis [24]. Unimportant candidate inputs can ensnare the data analysis as well as modeling without any additional useful information. Such unimportant features are, in a same concept, max-redundant or min-irrelative (which can be denied) [25]. However, the feature selection only by the mentioned criteria on maximum relevancy, fall off to select highly redundant candidates, i.e. the candidates which are highly correlated with each other. So, by proceeding based on these criteria and removing the redundant candidates, we cannot expect desired results from this filtering. Thus, minimization process will be added to redundant features to opt the non-redundant candidates.

In minimal – redundancy – maximal – relevance (mRMR) approach [26], the samples are chosen using the greedy procedure. This approach is a robust approach for choosing the desired feature, thought, we face another challenge in feature sorting which is impossibility of eliminating the chosen samples as well as existence of very useful information in the redundant features [27]. To deal with these issues, [27] has applied some approaches by using wrapper procedure, however, if a mixture of certain classifiers in wrapper procedure is not used, we will face some challenges. So, the chosen samples in this procedure are not able to be always considered the optimum features. To deal with this problem, we implemented a two-steps mutual information feature selection using a transductive procedure (MIT-MIT) that operates by learning and using unlabeled inquiry data. In order to enhance the forecast performance and achieve faster calculations in the suggested approach, some modifications are exerted to optimize the approach.

1.3. Contributions

Despite the reviewed prediction methods, a precise method is still needed. The aforementioned methods are not compared with other methods. This means, if the suggested procedures are used, getting optimum outcome should be targeted. In order to achieve this goal, we suggest a novel prediction procedure build on these additions:

a) Implementation of a novel feature selection technique to filter the input signal. The result of this elimination will be used as input for the forecast engine. The elimination in the aforementioned feature selection stage is formed on accurate information and smooth training input.
b) Introduction of the forecast engine with dint models using the NNs. A multi-block forecast engine can forecast the signal using the feature selection. All variables in these blocks are optimized using a novel intelligent algorithm to enhance the forecast engine precision and training speed.
c) Assessment of the suggested forecast engine forms in various approaches. In the proposed approach, we implemented various models of the suggested forecast engine with numerous mixes in order to obtain the optimum combined approach. Ultimately, the optimized mode forecast engine can be used as a solution for demand and price prediction.

1.4. Paper organization

The remaining parts of the paper are organized as follows. In Section 2, the main structure of proposed model is presented. Section 3, presents the proposed feature selection model. Section 4, proposed the forecast engine model. The proposed intelligent algorithm is presented in Section 5. The numerical results and analysis are presented in Section 6. Finally Section 7 concludes the paper.

2. Structure of forecast approach

In this paper, we suggest a multi block forecast engine using a novel approach called Elman neural network (ENN), which is taken into account in hybrid framework via forecast precision improvement. The mentioned assessments is used for obtaining distributed hybrid frameworks behavior best presentation's comparison using the error norm computation. The main structure of proposed model is presented in Fig. 1. As shown in this figure, the input signal is entered to feature selection and then to the forecast engine. Furthermore, the proposed forecast engine is optimized by an intelligent algorithm. All models of forecast approach are following this structure in the figure with different connections which is presented in the following sections. The steps of this flowchart can be summarized as:

Step 1: Input the signal and normalize