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A novel model: Dynamic choice artificial neural network (DCANN) for an electricity price forecasting system

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ABSTRACT

Big data mining, analysis, and forecasting always play a vital role in modern economic and industrial fields. Thus, how to select an optimization model to improve the forecasting accuracy of electricity price is not only an extremely challenging problem but also a concerned problem for different participants in an electricity market due to our society becoming heavily reliant on electricity. Many researchers developed hybrid models through the use of optimization methods, classical statistical models, artificial intelligence approaches and de-noising methods. However, few researchers aim to select reasonable samples and determine appropriate features when forecasting electricity price. Based on the Index of Bad Samples Matrix (IBSM), a novel method to dynamically confirm bad training samples, and the Optimization Algorithm (OA), DCANN and Updated DCANN are proposed in this paper for forecasting the day-ahead electricity price. This model is a hybrid system of supervised and unsupervised learning and creatively applies the idea of deleting bad samples and searching quality inputs to develop and learn, which is unlike BPANN, RBFN, SVM and LSSVM. Numerical results show that the proposed model is not only able to approximate the actual electricity price (normal or high volatility) but also an effective tool for h-step-ahead forecasting (h is less than 10) compared to benchmarks.

1. Introduction

With the development of information technology and the arrival of big data, researchers have mastered a large number of data and hope to establish an appropriate model to analyze these data, mining the useful information, so as to make quantitative prediction. A good prediction model can not only utilize data resources more reasonably but also avoid a waste of benefits and resources. Therefore, how to select the best forecasting model for electricity price is a remarkable problem due to our society becoming heavily reliant on electricity. After the electric power industry restructured, different participants, including generation companies and electricity consumers, typically meet in a marketplace to make a decision about electricity pricing [1]. The behavior of each participant also directly affects his or her (or its) own benefit. Therefore, a good forecasting system for electricity prices and demand has emerged as a major research field in electrical engineering in the current deregulated scenario; many researchers and academics are currently developing methods and approaches to forecast price and load [2]. To show the significance of the primary idea of this paper, various effective forecasting approaches for electricity prices that have already been researched will be introduced in the following.

Keynia proposed a new forecast strategy that has a new method of two-stage feature selection, a composite neural network and some predictors. Additionally, a cross-validation technique is presented to fine-tune the adjustable parameters that belong to the feature selection approach and the CNN [3]. Anbazhagan and Kumarappan recommended a day-ahead electricity price classification that could be realized using a three-layered feed-forward neural network (FFNN), a cascade-forward neural network (CFNN) and a generalized regression neural network (GRNN); they also presented a discrete cosine transforms (DCTs)-based neural network (NN) approach (DCT–NN) to classify the electricity markets of mainland Spain and New York [4,5]. A hybrid ARFIMA and neural network model is investigated for electricity price prediction by [6]. Cifter uses both the Markov-switching generalized autoregressive conditional heteroskedasticity (MS-GARCH) model and a set of different volatility models to forecast electricity price behaviors in the Nordic electric power market [7]. A new fore-

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casting model that detaches high volatility and daily seasonality for electricity prices based on the Empirical Mode Decomposition, Seasonal Adjustment and Autoregressive Integrated Moving Average is proposed by Dong et al. [8]. Instead of using point forecasts, Khosravi et al. employed the delta and bootstrap methods for construction of prediction intervals (PIs) for uncertainty quantification. Then, they proposed a novel hybrid method for the construction of high-quality prediction intervals (PIs) for electricity prices [9,10]. Lei and Feng proposed a novel gray model called PGM (1, 2, a, b) to improve the performance of traditional grey models for short-term electricity price prediction in competitive power markets [11]. A two-stage hybrid model based on panel cointegration, which utilizes information of inter-temporal dynamics and the individuality of interconnected regions, and a particle filter (PCPF) is proposed by Li et al. [12]. Liu and Shi applied various autoregressive moving average (ARMA) models with generalized autoregressive conditional heteroskedasticity (GARCH) processes, along with their modified forms, ARMA–GARCH-in-mean, to address the issue of forecasting hour-ahead electricity prices [13]. Sharma and Srinivasan examined electricity price time series from a dynamical system perspective and proposed a hybrid model that employs a synergistic combination of a Recurrent Neural Network (RNN) and a coupled excitable system for prediction of future prices in deregulated electricity markets [14]. Seeking more accurate price forecasting techniques, Shayeghi and Ghasemi proposed a new combination of a Feature Selection (FS) technique based on the mutual information (MI) technique and the Wavelet Transform (WT) used in this study. [15]. Extreme Learning Machine (ELM), which is a novel neural network technique, is investigated by Shrivastava and Panigrahi in the price-forecasting problem [16]. Yan and Chowdhury presented a hybrid mid-term electricity market clearing price (MCP) forecasting model combining both LSSVM[1] and auto-regressive moving average with external input (ARMAX) modules [17]. Zhang et al. proposed a new hybrid method based on wavelet transform (WT), autoregressive integrated moving average (ARIMA) and an LSSVM optimized by particle swarm optimization (PSO) and another hybrid forecast technique based on wavelet transform (WT), a chaotic least squares support vector machine (CLSSVM) and an exponentially generalized autoregressive conditional heteroskedastic (EGARCH) model to predict electricity prices [18,19]. Nima Amjady and Farshid Keynia proposed a strategy which includes a new closed loop prediction mechanism composed of probabilistic neural network (PNN) and hybrid neuro-evolutionary system (HNES) forecast engines to forecast PJM electricity price [20]. Grzegorz Dudek applied Multilayer perceptron for GEFCom2014 probabilistic electricity price forecasting [21]. Ioannis and Athanasios S reviewed recent literatures related to electricity price forecasting and applied ANN to predict future electricity price [22]. Feijoo et al. presented the K-SVR which is a hybrid model that combines clustering algorithms, support vector machine, and support vector regression to forecast electricity price of PJM [23]. Abedinia et al. proposed a Combinatorial Neural Network (CNN) based forecasting engine to predict the future values of price data [24]. He et al. proposed curvelet denoising based approach to improve forecasting effectiveness of electricity price [25]. Ziel et al. introduced an econometric model for the hourly time series of electricity prices of the European Power Exchange (EPEX) which incorporates specific features like renewable energy [26]. Babu et al. developed a combination forecasting model ARIMA-ANN to merge advantages from linear and non-linear forecasting model [27]. Weron reviewed literatures related to electricity price forecasting and looked ahead and speculated on the directions electricity price forecasting would or should take in the next decade or so [28], in which more literatures can be found.

Regarding the related works mentioned above, most of them developed a new hybrid model through the use of optimization methods (PSO, GA and so on), classical statistical models such as ARIMA, ARMAX and GARCH, artificial intelligence approaches (BPANN,[2] SVM, RNN, ELM) and de-noising methods such as WT and EMD. After reviewing the literature related to electricity price forecasting, we will give the core idea of this paper via a simple introduction to general forecasting models.

Searching a forecasting model is identical to finding a map f that can let *input* be *output* and be described by the following expression:

$$output = f(input)$$

Finding a reasonable f has always been critical in the forecasting process, and many researchers contribute to this searching process, as demonstrated above. However, researchers tend to concentrate on finding f such that an important issue is ignored, which is the rationality of *input* and *output* or the rationality of samples; many studies construct training samples directly without checking if this construction is reasonable. For example, if a machine, which is regarded as a forecasting model in this paper, learns something incorrect, its effectiveness may not be adequate for its users. How to construct a model that can learn correctly is the inspiration of this paper, and this is also an important process when forecasting electricity prices. In existing literatures, feature selection (FS) is a related technology to make machine learn correct features and has been widely applied in the field of electricity forecasting [3,20,22,28–38]. In general, FS approaches can be divided into two main classes: filter approaches and wrapper approaches. In the filter approaches, each selected subset is evaluated independently of a certain classifier and by applying just natural properties of the data. Whereas, the performance of a certain classifier, as a learning algorithm, is used for evaluating each subset in the wrapper approaches. Executing of filter approaches in comparison with wrapper approaches are computationally cheaper. Therefore, they are often suggested for FS in the high dimensional dataset [29,36,39]. According to above works related to feature selection, they always select concrete features to train the forecasting models without any process to determine whether training samples are reliable. Moreover, the selected features, commonly fixed, are assumed to be suitable for all training samples and outputs, which ignores that each output may have its corresponding proper input. To learn correctly and overcome both drawbacks of FS technologies, a new model aiming to dynamically select useful training samples for each desired output is proposed for forecasting electricity price by using an original index to identify bad samples; this method is named IBSM. Additionally, a novel dynamic choice artificial neural network (DCANN) based on IBSM is proposed to forecast electricity price.

Since the DCANN is a derived version of ANN, it has the same drawbacks with ANN, indicating that poor initial parameters of DCANN will result in unsatisfactory fitting errors [34]. For addressing this issue, many researchers applied optimization algorithms (OAs) to develop hybrid model to improve forecasting effectiveness, such as GA-ANN, PSO-ANN, CPSO-ANN and so on [16,34,40–46]. These OAs are always population-based algorithms that learn from the past searches by using a group of individuals or agents. There are three categories of OAs [47], which are 1) Evolutionary Programming (EP), and 2) Evolutionary Strategies (ES), and 3) Genetic Algorithms (GAs). The implementation

[1] Least Square Support Vector Machine.

[2] Back Propagation Artificial Neural Network.