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An Electricity Price Forecasting Approach Based on Dimension Reduction Strategy and Rough Artificial Neural Networks.

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ABSTRACT

The direct influence on power system management. Taking into account all of the important factors in deciding electricity rates, some of which are stochastic, is a difficult task. First, Grey Correlation Analysis is used to select the effective parameters in the EPF problem and remove redundant variables based on low correlation grades in this proposed method. After extracting the features, we use the PCA to reduce the data so that the related features can be used for classification. We'll use this to apply the two classifier comparisons. The first is with the ad boost, and then we use the neural networks classifier for stronger market forecasting predictions.

Keywords: Forecasting, ANN, local minima, Mean square Error.

2. INTRODUCTION

Market participants are facing new obstacles as a result of electricity sector liberalization and the global financial crisis. Both market participants must attempt to forecast the price of electricity in particular. As a result, a variety of models have been proposed in the literature to evaluate and forecast electricity prices over various time horizons and goals. Modeling of the electricity market price forecasting is a challenging task. It's important to remember that the price of energy is influenced by a variety of factors. Price forecasting techniques must, for this reason, take into account both production costs and market agents' strategic actions. However, in power markets around the world, this is a challenging task because the combination of both effects results in highly complex price dynamics. Seasonality, high volatility, and frequent spikes are all hallmarks of its evolution. This has contributed to the use of explanatory variables in some of the models proposed in the literature to help describe price distributions [1]. [2] Used multiple regressions with nuclear usable energy, gas price, rain, and temperature as repressors in addition to other modeling examples using exogenous variables. As a consequence, demand, weather, technology mix, and proxies for economic activity are some variables to consider in shaping price expectations. Furthermore, the price of electricity is influenced directly by Prices for fuel whose cost are increasing, especially in markets where coal and gas are the primary energy sources for electricity generation. Other circumstances, however, can only be attributed to wholesale market malfunctions. Competitive games (upward or downward) and incorrect demand forecasting are the most common triggers. Almost all live spot electricity markets have a mandatory day-ahead bidding system in place, which may or may not be supplemented by intra-day and real-time (balancing) markets. The day-ahead market is the most important spot (intra-day or real-time) market in terms of the volume of energy exchanged. In fact, the entire electricity industry's economics are heavily dependent on market-determined electricity prices. In electricity markets, where participants must optimize their positions (bidding price and quantity for different markets, including day-ahead and intraday) based on their perception of future hourly prices and incremental costs over the bidding period, electricity price forecasting is particularly relevant in the short run (from three to 24 hours). Furthermore, some agents, particularly large consumers with self-power output, have the ability to choose whether a portion of their consumption is to be met by the market or by their own production, as well as the timing for each. Regardless, the maximization of benefit is the guiding force behind the decisions of all market participants.

Fig1: Factors Analysis For price Forecasting

The problem of electricity price forecasting is said yet distinct from that of electricity load forecasting. Although the demand (load) and thus the worth are correlated, their relation is non-linear. The load is altered by the factors like non- storability of electricity, consumers' behavioral patterns, and seasonal changes in demand. The price, on the opposite hand, is suffering from those aforesaid factors also as additional aspects like financial regulations, competitors' pricing, dynamic market factors, and various other macro- and micro economic conditions. As a result, the worth of electricity may be a lot more volatile than the electricity load. Interestingly, when effective pricing strategies are introduced, prices become even more volatile, where the daily average price changes by up to 50% while other commodities may exhibits about 5% change [9]. Load forecasting has progressed to some extent where the loads are often predicted with up to 98% of accuracy in some cases [6]. However, current state-of-the-art approaches in price forecasting are at the most about 95% accurate [4]. Thus, a more accurate price forecasting system is important since many retailers and their businesses depend upon the costs of electricity. Our objective is to create an accurate electricity price forecasting model for generating hour-ahead price forecasting. This price forecasting is vital for the transmission com- pany to schedule short-term generator outages, design load response programs also as bid into the market strategically and manage its assets optimally. When accurate price forecasting system is out there, large consumers can stem their electricity usage plan strategically to maximize their utility.

Numerous papers have been published in the area of price forecasting using Artificial Neural Network (ANN) for price forecasting. Here, our main contribution lies on extracting the simplest features from a pool of features and training the ANN with these features so as to make a real-time forecasting model. As mentioned in [4], lagged prices are generally utilized in price forecasting since its high autocorrelation with electricity market prices. However, during a real-time setup, aside from the system load and price during the previous hour, no other features are available, thus restricting us to features from the available pool. Even though a lot of research has been performed on electricity price forecasting, none of the experiments provides adequate accurate model with less than 5% mean absolute prediction error (MAPE) value. This indicates there's still room for improvement. It should be noted that some models proposed performed well in certain electricity markets whereas an equivalent model shows very bad results which leads to a different market. A simple general model which may forecast in many markets with a good level of accuracy is our aim.

3. EXISTING WORK

The authors of [1] use fundamental models in the electricity sector for forecasting. Since the model represents demand and supply, these models reliably predict energy prices. Artificial Neural Networks (ANN) and econometric time series models have recently been developed, as well as machine learning methods. The ANN model, on the other hand, is prone to being stuck in local minima, which is considered its most serious flaw. Forecasting electricity price accurately becomes a challenging job in [3] due to dynamic drivers and sharp shifts in the price of electricity. In current applicable models, there are two key issues. To begin with, a hybridized model coupled with Empirical Mode Decomposition (EMD) has a drawback, which decreases the model's accuracy. Second, when combined with linear and non-linear models, the aforementioned model is unable to characterize the characteristics of electricity price.

4. INPUT DESIGN AND OBJECTIVES

Input Design: The input design is that the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to place transaction data in to a usable form for processing are often achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the information directly into the system. The design of input focuses on controlling the quantity of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such, how in order that it provides security and ease of use with retaining the privacy. Here the given Input Design things are what data should be given as input? How the data should be organized or coded? The dialog to guide the operating manpower in providing input.

Objectives:

- Input Design is the process of converting a user-oriented illustration of the input into a computer-based system. This design is vital to avoid errors within the data input process and show the right direction to the management for getting accurate information from the computerized system.
- It is achieved by creating easily operated screens for the data entry to handle large volume of data. The goal of designing input is to form data entry easier and to be free from anomalies. The data entry screen is meant in such how that each one information manipulates are often performed. It also provides record viewing facilities.
- When the data is entered it will examine for its validity. Data can be entered with the help of visual display unit. Appropriate messages are provided as when required in order that the user won't be in maize of instant. Thus the objective of input design is to make an input layout that is easy to follow.

5. OUTPUT

A standard output is one, which meets the requirements of the end user and gives the information clearly. In any system outcome of processing are communicated to the users and to other system through outputs. In output outline it is determined how the information is to be override for immediate need and also the text output. It is the utmost important and direct source data to the user. Well organized and intelligent output design improves the system's relationship to assist user decision-making.

(i) Designing computer output should proceed in an organized, well thought out manner; the proper output must be developed while ensuring that every output element is designed in order that people will find the system can be used easily and effectively. When analyses design computer output, they ought to identify the precise output that is needed to satisfy the requirements.

2. Select methods for presenting information.

(ii) Create document report, or other formats that contain information produced by the method.

The output kind of a data system should accomplish one or more of the subsequent objectives. Convey information about the past jobs, current status or projections of the future. Signaling important events, opportunities, problems, or warnings, trigger an action, Confirm an action.

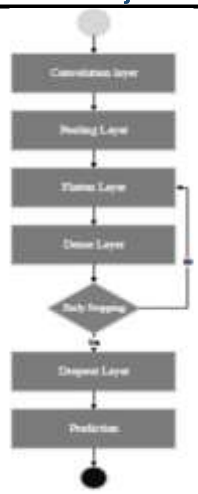

Fig 2: System Architechture

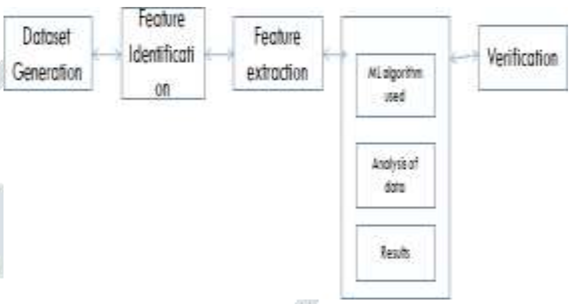

Fig 3:- data flow diagram

6. METHODOLOGY

XGBOOST:EXTREMEGRADIENT BOOSTING

Be related with a residual (y – F0)

A new model h1 is fit to the residuals from the previous step

Now, F0 and h1 are combined to offer F1, the boosted version of F0. The mean squared error from F1 are going to be less than that from F0:

To improve the performance of F1, we could model after the residuals of F1 and make a replacement model F2:

$$F_2(x) <- F_1(x) + h_2(x)$$

This can be done for 'm' iterations, until an initial model F0 is defined to predict the target variable y. This model will residuals have been minimized as much as possible:

$$F_m(x) <- F_{m-1}(x) + h_m(x)$$

Here, the additive learners don't disturb the functions created within the previous steps. Instead, they communicate information of their own to bring down the errors.

a) LSTM NETWORK

Deep learning or deep structured learning are often defined as special quite of neural networks composed of multiple layers. These networks are better than traditional neural network in preserving the knowledge from previous event. Recurrent neural network (RNN) is one such machine that features a combination of networks in loop. The networks in loop allow the information to keep on. Each network in the loop takes input and information from previous network performs the specified operation and produces output along with passing the information to next network. Some applications require only recent information while others may ask for more from past. The common recurrent neural networks lag in learning because the gap between required previous information and therefore the point of requirement increases to an outsized. But providentially Long Short Term Memory (LSTM) Networks [18], a special form of RNN are capable in learning such scenarios. These networks are precisely designed to escape the long term dependency issue of recurrent networks.

LSTMs are good in remembering information for while. Since more past information may affect the accuracy of model, LSTMs become a legitimate choice of use. Distinctive LSTM module called repeating module has four neural network layers interact in a unique fashion as shown in Fig. 1. The module segment has three gate activation functions σ1, σ2, and σ3 and two output activation functions ϕ1 and ϕ2 as depicted in Fig. 1. The symbol π and Σ represent element wise multiplication and addition discretely. The concatenation function is represented by symbol (•) bullet. The foundational component of LSTMs is cell state, a line running from Memory from Previous Block (S t−1) to Memory from Current Block (S t). It allows the information to run straight down the line. Network can decide the quantity of previous information to flow. It is controlled through first layer (σ1). The operation performed by this layer is given in (2).

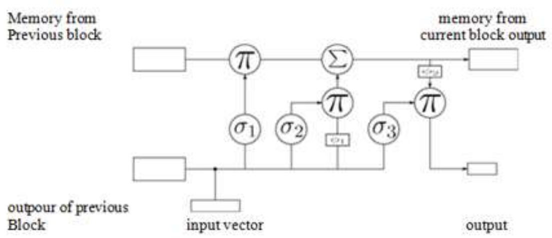

Fig 4: Repeating Module of LSTM

The new information to be stored in cell state is determined using two network layers. A sigmoid layer (σ2) that decides values to update (It) (see (3)) and tanh layer ϕ1 that progress a vector of latest candidate values (S˜t) as shown in (4). The combination of both to be added within the state. Finally cell state is updated using (5).

b) PREDICTION USING LSTM-RNN

The subsequent workload information is one among the essential parameters in dynamic resource scaling. The efficient resource scaling leads a system to be cost effective. A good resource scaling method also helps in reducing the power consumption by shutting off unused resources. Thus the system becomes eco-friendly too.

In the proposed model output of predictive unit is fed into a device called resource manager that also takes the current state of datacenter into account before taking resource scaling decisions as shown in Fig. 2. If available

1 Set ip units, lstm units, op units and optimizer to define Long Short-Term Memory Network (L)

2: Normalise the dataset (Di) into values from 0 to 1 using (6)

3: Select training window size (tw) and organize Di accordingly

4: for n epochs and batch size do

5: Train the Network (L)

6: end for

7: Run Predictions using L

8: Calculate the loss function using (7)

Figure 3: Pseudocode for price forecasting Prediction using LSTM

7. RESULTS

Fig. 5: Actual hourly Electricity price and weekly rolling mean graph

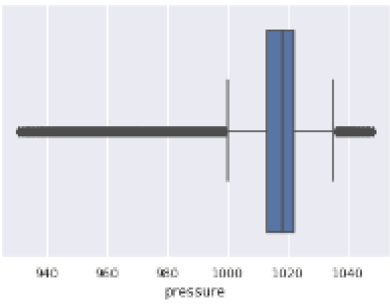

Fig 6: The figure above indicates that 10mpa corresponds pressure.

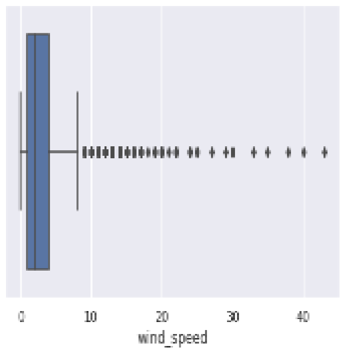

Fig 7 : As before, take a cautious approach. We'll leave the values in 'wind speed' as NaNs.

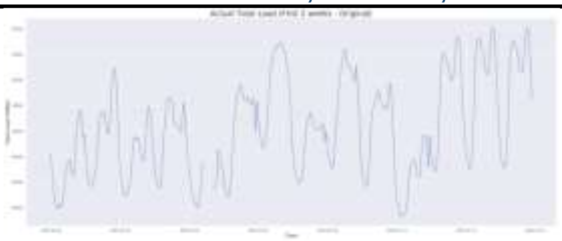

Fig8: The (resampled) monthly frequency of the actual electricity price, as well as its 1-year lagged monthly frequency, is shown in the graph above.

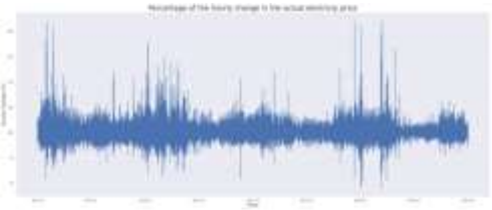

Fig 9: The difference in the actual price from hour to hour, as seen in the graph above, is usually between -25 percent (actual price * 0.75) and +25 percent (actual price * 1.25).

Fig 10: Here plotted the actual hourly electricity price a periodicity from week to week in the graph above; here the electricity prices are higher during business days then as usual during holidays. Since the price is higher during the day and lowers at night, it has an intraday periodicity.

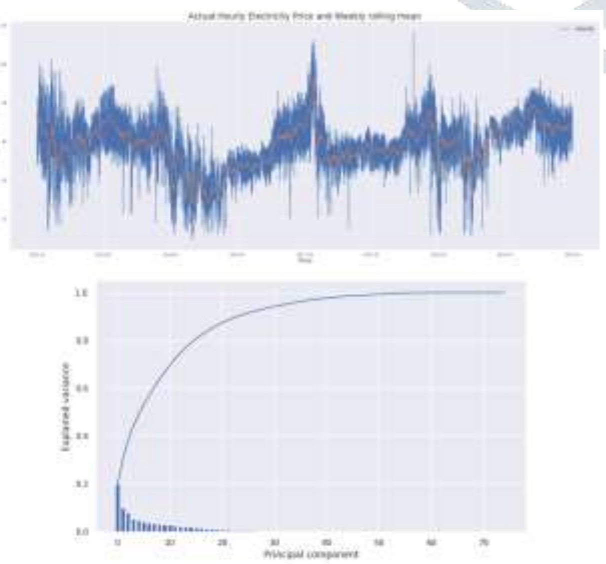

Fig11: principal component analysis with data reduction and variance

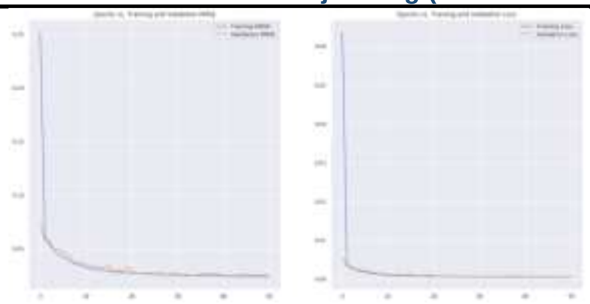

Fig 12: RMSE for Training and validation and validation loss for model LSTM

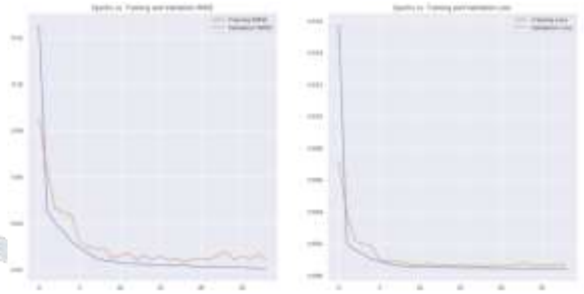

Fig 13: RMSE for Tanning and validation and validation loss for model CNN

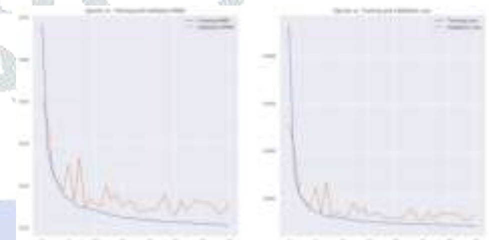

Fig 14: RMSE for Training and validation and validation loss for model Encoder-Decoder model

Model	RMSE
XGBoosting	3.214
LSTM	2.965
CNN	2.324
Encoder-Decoder	2.296

Table1: RMSE Analysis table for all the four models so The CNN-encoder and decoder model gives better accuracy in terms for root mean square error ratio

8. CONCLUSION

CNN is a popular tool for predicting short-term EPF. While ANN is used for classification, it employs the back propagation algorithm, which increases the algorithm's complexity. Over fitting happens when an ANN takes on so many functions. Local minima are quickly trapped by ANN. We suggest a model for short-term EPF using CNN and PCA in this paper. From the findings, the proposed model is compared to benchmark models, and it is concluded that the proposed model outperforms the benchmark method.

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