VISVESVARAYA TECHNOLOGICAL UNIVERSITY

'JNANA SANGAMA' BELAGAVI-590 018, KARNATAKA

PROJECT PHASE 1 REPORT

ON

"ELECTRICITY PRICE FORECASTING USING DEEP LEARNING"

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE,

BACHELOR OF ENGINEERING
IN
COMPUTER SCIENCE & ENGINEERING

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CONTENTS

1.Introduction:

The excessive electricity produce is a difficult task, as extra electricity storage is found to be difficult and challenging too. So, the generation of a system is necessary, which accurately predict the electricity consumption and minimize production and storage of the electricity issue. Such system can help for the production and the utilization of electricity optimization. This decreases the electricity usage costsfor each individual household with help of improvedproduction scheduling and electricity purchase in advance . In a deregulated competitive electricity market, an electricity price, forecasted a week ahead, isone of the most important concerns of the market participators. During bidding, market participators can adjust their bidding, based on the forecasted price to gain more profit. The consumer can also manage electricity usage, based on the hourly electricity price,. For the power generating party, bidding strategy determines the level of profit, and the accurate prediction of electricity price could make it possible to determine a more accuratebidding price. This cannot only reduce transaction risk, but also seize opportunities in the electricity market.

The value of electric power is now reflected in its price, which should be determined by the market. According to market value determination rules, changes in the supply and demand situation determine the constantly changing price of electricity. If electricity prices could be accurately predicted, power system dispatching could be carried out reasonably and effectivelyaccording to the price of power, and ensure the safe and reliable operation of the electricity system.

Power generators could use electricity price forecasting to assist in the formulation of bidding strategies; power users could rationally arrange production activities according to their own needs and reduce to cost of electricity in production; from this we can see that the research on electricity price forecasting has practical significance. The so-called electricity price forecasting takes into account power cost influencing factors such as the power supply and demand relationship, market participant influences, power generation costs, and market structures.

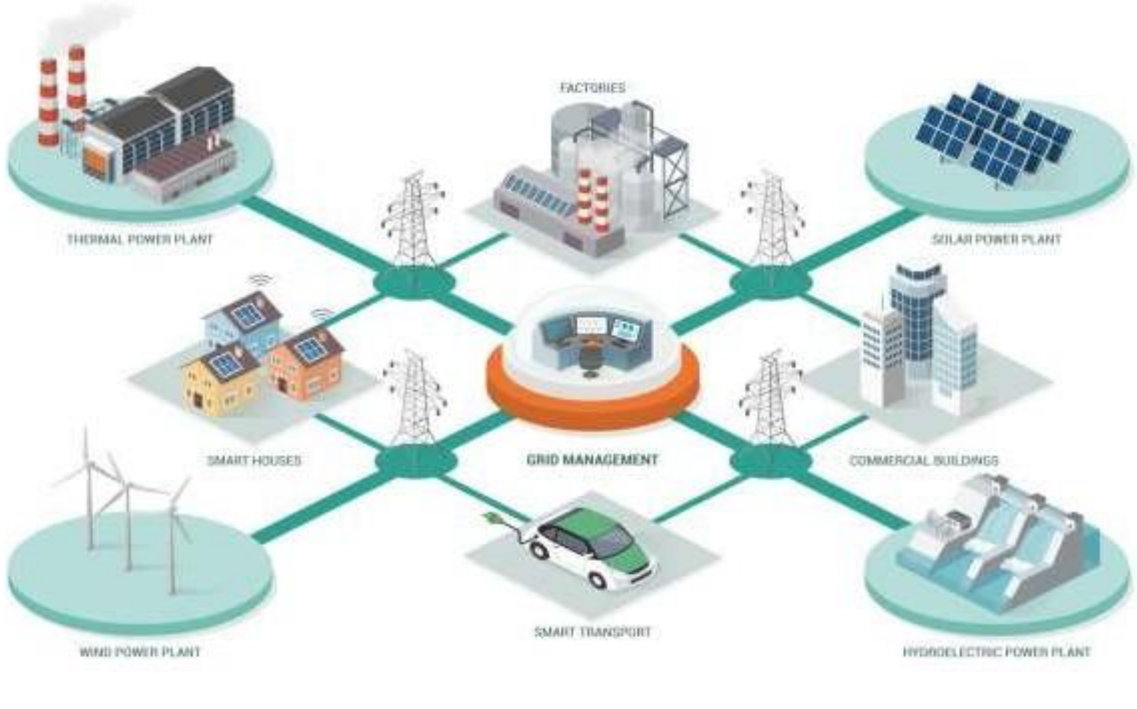
2. PROBLEM STATEMENT

- Energy is transferred between several networks, there are numerous bidding techniques, the price of electricity is non-linear and extremely variable, and both supply and demand are always changing. Storage is therefore unprofitable.

3.OBJECTIVES

- This study is to evaluate the peak performance of different ML Algorithms & Deep neural networks in predicting the price of electricity.
- To provide an optimized scheduling process for an industrial loads to get an accurate electricity price.
- Comparing ML & DL algorithms, the high accurate model for EPF is selected.

4. SCOPE OF THE PROJECT



- Large power plants like thermal, solar, wind, and hydroelectric power plants produce electricity. The electricity is then delivered to other units, including smart homes, factories, smart transport and commercial buildings via transmission lines.

5. LITERATURE SURVEY

“Electricity Consumption & Prediction using Machine Learning Models”.

Tapas Ranjan Jena [1] narrated that research has the objectivity to analyse Machine Learningalgorithms effectiveness, after being applied to the electricity consumption prediction.Load management and demand response, high dimensional data sets are much effective variable selection, accurate prediction for electricity market pricing. This Paper reviews the Conventional Machine Learning Models as well as the recent models, allowing predicting electricity consumption. The predictions are proposed for the research reference, depending upon previous work analogy.

“Day-ahead electricity price prediction applying hybrid models of LSTM-based deep learning methods and feature selection algorithms under consideration of market coupling”.

Denis Beckera [2] told that Their study provides a method of exploring the influence of market coupling on electricity price prediction. We applystate-of-the-art long short-term memory (LSTM) deep neural networks combined with feature selection algorithmsfor electricity price prediction under the consideration of market coupling. LSTM models havea good performance in handling nonlinear and complex problems and processing time series data. In our empirical study of the Nordic market, the proposed models obtain considerably accurate results. The results show that feature selection is essential to achieving accurate prediction, and features from integrated markets have an impact on prediction.

“Week Ahead Electricity Price Forecasting Using Artificial Bee Colony Optimized Extreme Learning Machine with Wavelet Decomposition”.

Udaiyakumar S [3] , a novel electricity price forecasting method is presented, based on the Artificial Bee Colony optimized Extreme Learning Machine (ABC-ELM) with wavelet decomposition technique. This has beenattempted with two different input data formats. Each data format is decomposedusing wavelet decomposition, Daubechies Db4 at level 6; all thedecomposed data are forecasted using the proposed method and aggregate is formed for the final prediction.This prediction has been attempted in three different electricity markets, in Finland, Switzerland and India. The forecasted values of the three different countries, using the proposed method are compared with various othermethods, usinggraph plots and error metrics and the proposed method is found to provide better accuracy.

“An Electricity Price Forecasting Model by Hybrid Structured Deep Neural Networks”,

Ping-Huan Kuo [4], this paper proposes an electricity price forecasting system based on the combination of 2 deep neural networks, the Convolutional Neural Network (CNN) and the Long Short Term Memory (LSTM). In order to compare the overallperformance of each algorithm, the MeanAbsolute Error (MAE) and Root-Mean-Square error (RMSE) evaluating measures were applied in the experiments of this paper. Experiment results show thatcomparedwith other traditional machine learning methods, the prediction performance ofthe estimating model proposed in this paper is proven to be the best. By combining the CNN and LSTM models, the feasibility and practicality of electricitypriceprediction is also confirmed in this paper.

“Deep Learning Forecasts of the Electricity Price with special Consideration of theElectricity

Supply”

Stephan Schneider [5] . This study primarily looks at the supply-side prediction of the electricity price with the help of deep learning artificial neural networksand thus makes a contribution to the literature. Autoregressive modelsand regressionsserve as benchmarks.

"Short-Term Electricity Price Forecasting by Employing Ensemble Empirical Mode Decomposition and Extreme Learning Machine", Sajjad Khan [6]. This study presentsa three-stage short-term electricity price forecasting model by employing ensemble empirical mode decomposition (EEMD) and extreme learning machine (ELM). In the proposed model,the EEMD is employed to decompose the actual price signals to overcome the non-linear andnon-stationary components in the electricity price data. Then, a day-ahead forecasting is performed using the ELM model. We conduct several experiments on real-time data obtained from three different states of the electricity market in Australia, i.e., Queensland, New South Wales, and Victoria. We also implement various deeplearning approaches as benchmark methods, i.e., recurrent neural network, multi-layer perception, support vector machine, and ELM. In order to affirm the performance of our proposed and benchmark approaches, this study performs several performance evaluation metric, including the Diebold–Mariano (DM) test. The results from the experiments show the productiveness of our developed model (in terms of accuracy) over its counterparts.

6. METHODOLOGY

In various different countries, electricity is traded in spot and derivative marketssimilar to that of a commodity. However, unlike most products, electricity is non-storable, and a stable power system is required to achieve a balance between power supply and demand. Due to the high volatility of electricity price, market participants are constantly exposed to high risks. In addition, many different unforeseeable factors contribute to electricity price adjustments, such as sudden changes in weather conditions, transmission problems in the power system etc. It canbe seen that because of the various factors influences electricity prices, there is a certain degree of difficulty in forecasting electricity prices. In order to solve the above problems, we proses a hybrid structured deep neural network model to conduct accurate electricity price analysis and forecasting

MODEL TRAINING

Walk Forward Nested Cross-Validation:

To avoid over-fitting, it is common to include a validation set to evaluate the generalization ability of the training model. The cross-validation is referred to as a method for tuning the hyper parameters and producing robust measurements of model performance. In [62], a nested cross validation procedure was introduced, which considerably reduced the bias and provided an almost unbiased estimate of the true error. Because new observations become available over time, in time series modeling, we implemented a walk forward nested cross-validation in which the forecast rolls forward in time. More specifically, we successively considered each day as the test set and assigned all previous data to the training set (Outer loop). The training set is split into a training subset and a validation set. The validation set data comes chronologically after the training subset (Inner loop). Walk forward validation involves moving along the time series one time step at a time. The process requires multiple models to be trained and evaluated, but the additional computational cost will provide a more robust estimate of the expected performance of the predictive model on unseen data.

Data Division:

We divided the whole database into two subsets: a training set and a test set. The training set includes a training subset and a validation subset, as shown in the dashed box in Figure 9. We initially apportioned the data set into training, validation, and test sets, with an 80-10-10 split. The magnitude of the test and validation set is anchored during the walk-forward test. Data processing: For neural network model training, the input data is usually normalized to the intervals [0,1]. This is not only done because the normalized data will require less time to train, but the prediction performance will also increase. In addition, we linearly interpolate the missing data and eliminate duplicates due to daylight saving.

Ten Experiments Training Algorithms::

for deep learning models have usually required the initialization of the weights of neural networks from which to begin the iterative training [63]. The random initial conditions for an LSTM network can result in different performances each time a given configuration is trained. Thus, we employed ten experiments for each model toreduce the impact of the variability on performance evaluation. Models were evaluated after taking the average of the experiments.

MODEL CONFIGURATION PARAMETERS

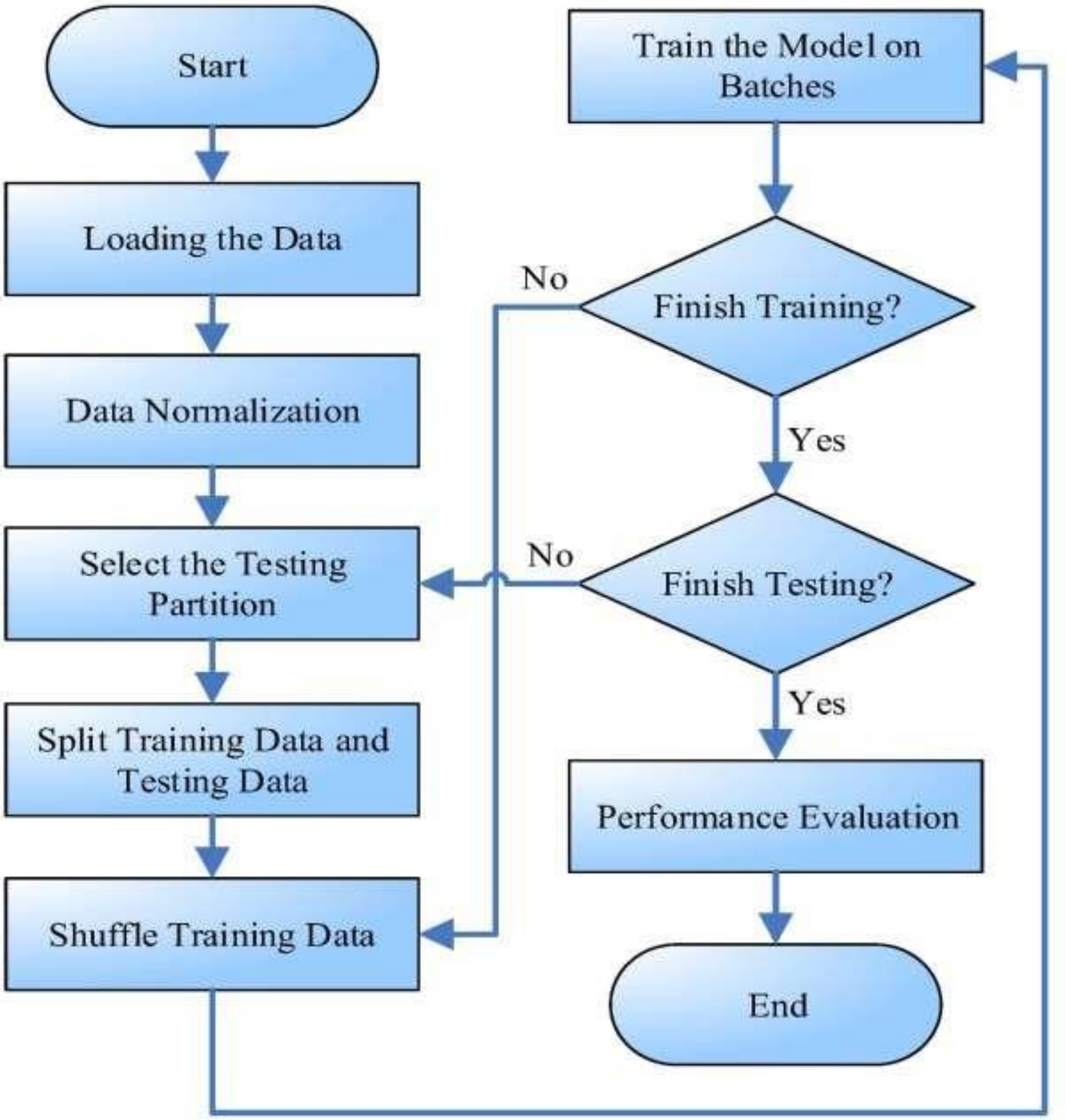
Parameters of Feature Selection:

The feature selection stopping criterion varies by algorithm, which is controlled by the parameters of models. The applied configuration of PSO was [c1: 0.5, c2: 0.3, ω: 0.7], and the stop condition is satisfied after 10,000 iterations. For GA, the crossover possibility and mutation possibility were set to 0.5 and 0.2, respectively. The population size was 100, and the maximum number of generations was 10,000. On the basis of the predictive ELM, the amount of the selected features by PSO-ELM and GA-ELM was automatically set to 30. For the sake of input consistency, the magnitude of the selected features of the rest of the models was set to 30 as well. For the PC method, we ranked all features attributable tothe correlation coefficients and selected the first 30 features. In terms of RFESVR, we ranked features by importance, discarded the least important features, and refit the model until 30 features remained. The regularisation parameter, λ, in Lasso regression was 0.0

Network Hyper Parameters:

Our study aimed to investigate the applications and impacts of different types of feature selection methods in a predictive LSTM architecture. We used a coherent configuration of a specific LSTM model for comparison and did not perform an extensive hyperparameter optimisation to search for the optimal configuration. After an inexhaustive grid search, we constructed our prediction model from an LSTM model with a single hidden layer of 300 units, followed by a fully connected dense layer with 100 neurons that preceded the output layer..

The LSTM encoder has a hidden layer with 300 units. In the CNN-LSTM Encoder- Decoder model, the CNN encoder has two convolutional layers, with 96 units to amplify any salient features, followed by a max-pooling layer. In the ConvLSTM Encoder-Decoder model, the encoder is a convolutional layer with 64 units. The input sequence length is 14 days (2weeks, commonly used in EPF). The optimizer is the Adam algorithm, and the loss function is Mean Squared Error (MSE).



7. EXPECTED OUTCOME

➢The literature survey concludes with better results for electricity consumption prediction with the hybrid approach of machine learning techniques.

➢Feature selection is essential to achieving accurate prediction, and features from integrated markets have an impact on prediction.

➢using graph plots and error metrics and the proposed method is found to provide better accuracy.

8. REFERENCES

[1] "Electricity Consumption & Prediction using Machine Learning Models", Tapas Ranjan Jena, Swati SucharitaBarik, SasmitaKumariNayak, published an Article - June 2020

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