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Power Price Forecasting In the Smart Grid Using Differential Evolution Based SVM Classifier

Ramya Devi. C¹, Amudha. L²

P.G. Student, Department of Computer Science and Engineering, K.Ramakrishnan College of Engineering,

Samayapuram, Trichy, Tamilnadu, India¹

Assistant Professor, Department of Computer Science and Engineering, K.Ramakrishnan College of Engineering,

Samayapuram, Trichy, Tamilnadu, India²

ABSTRACT: Power price forecasting is a significant part of smart grid because it makes smart grid cost efficient. The existing methods for price forecasting may be difficult to handle with huge price data in the grid since the redundancy from feature selection cannot be averted. To solve such a problem, a novel electricity price forecasting model is Hybrid feature Selection, Feature Extraction and Classification (HSEC) are integrated into a single framework design. In this novel model, first, a Grey Correlation Analysis (GCA) based Hybrid Feature Selector (HFS), combining Relief-F algorithm and Random Forest (RF) is designed to calculate the feature importance and control the feature selection. For feature extraction, Kernel Principle Component analysis is used to further reduce the redundancy among the selected features. Finally, design a differential evolution (DE) based Support Vector Machine (SVM) classifier for to forecast the price accurately.

KEYWORDS: Price forecasting; Feature Selection; Classification; Smart grid

I. INTRODUCTION

One of the main goals of smart grid is to reduce power peak load and to balance the gap between power supply and demand [1]. Customers are able to partake in the operations of smart grid, where the energy cost can be reduced by energy preservation and load shifting. In this case, dynamic pricing is a key indicator of users' switching load [1].Generally, accurate point price forecasting is expected because of the requirement of economy and industry [2].As for customers, they are actually eager to know whether the electricity price exceeds the specific customer-defined thresholds, which they used to decide to turn the load on or off. Under this circumstance, customers require the electricity price classification. Hence, some specific thresholds based on point price forecasting algorithms are used to classify the electricity price. Function approximation techniques are the fundamental of point price forecasting algorithms, in which the basic process of price formation is imitated by a price model [3]. Moreover, price classification requires lower accuracy. Thus, electricity price classification becomes a key priority in the price forecasting.

II. RELATED WORK

In [2] authors describe a smart grid is characterized by the bi-directional connection of electricity and information flows to create an automated, widely distributed delivery network. In [3] authors many technologies to be adopted by smart grid have already been used in other industrial applications, such as sensor networks in manufacturing and wireless networks in telecommunications, and are being adapted for use in new intelligent and interconnected paradigm. In [4] authors a forecasting methodology for prediction of both normal prices and price spikes. In the day-ahead energy market is proposed. In [5] authors the proposed approach uses a wavelet transform (WT) combined with



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ARIMA, a neural network (NN), a compound classifier and a k-nearest neighbor model (k-NN) to separately implement normal price and price spikes forecasting processes. In [6] authors WT deals with non-stationary by decomposing the price series into less volatile components. The ARIMA model captures cyclicality of the series clearly exhibiting hourly and weekly patterns.

III. PROPOSED ALGORITHM

To enhance the accuracy of the proposed framework, first develop a parallelized hybrid feature selector (HFS), a Kernel Principal component analysis (KPCA) and a Differential Evolution based Support vector Machine (SVM). HFS based on Grey Correlation Analysis combining Random Forest (RF) and Relief-F algorithm. These two algorithms are used to calculate the feature importance and control the feature selection. Then KPCA is applied to perform the non linear dimension reduction. KPCA will be performed in the selected features for further removal of redundant features.Finally, the selected features is sent to build SVM. The support vector is a classifier that tries to find a hyper plane which can divide data into the correct classes .Since SVM is controlled by several super parameters(cost penalty, insensitive loss function parameter and kernel parameter) so that DE algorithm is used to tune the super parameters. SVM is an underpinned framework that can predict the price efficiently.

Power Price Forecasting has modules are

- Hybrid Feature Selection
- Hybrid Feature Extraction
- Clustering
- Classification
- Predicted Data

A. Hybrid Feature Selection

Feature selection is performed based on GCA algorithm. It is kind of preprocessing of a dataset value. That will remove noisy inconsistent data. Thus GCA can provide a quantitative measure of the closeness between the electricity prices.

B. Hybrid Feature Extraction

The features selected by HFS can be considered that have no irrelevant features, but also have redundant features. Kernel Principle Component Analysis (KPCA) for feature extraction ,which reduce the redundancy among features.

C. Clustering

Clustering is the grouping of a particular set of objects based on their characteristics, aggregating them according to their similarities.

D. Classification

Support Vector Machine (SVM) underpinned framework that can predict the price efficiently.SVM is a classifier which can divide features into the correct classes. The four main procedures run repeatedly until the optimal parameters are obtained.

1. Initialization

This stage forms the first population randomly. We make the first population obey the uniform distribution.

2. Mutation

The target of mutation operation is to generate new individuals.

3. Crossing

Crossing is to increase the variety of generation and mix the mutant individuals via the origin individuals in every dimension with a certain probability.



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4. Selection

The selection operation selects the individuals that make SVM more accurate.

E. Predicted Data

In this module, can get our predicted data by performing above methodologies from huge amount of dataset.

IV. PSEUDOCODE

Input: WR[Tk] 0:0;WF [Tk] 0:0;A[];R[n] Output: WR[Tk];WF [Tk] 1 begin 2 initialization: set all weight WR[Tk] <- WF[Tk] <- 0:0, read data from A[] 3 Evaluator &: 4 begin 5 for k from 1 to m do 6 for i from 1 to n do 7 calculate errOBB1i using corresponding OBB data set of decision tree[i] 8 randomly add noise to all OBB data on feature Tk 9 calculate errOBB2i using corresponding OBB data set of decision tree[i] 10 end calculate the importance of feature WR[Tk] <- (errOBB2i□errOBB1i)/n 11 12 end 13 end 14 Evaluator : 15 begin 16 for k from 1 to m do 17 select an item in class (Ci) by random 18 find k nearest hits item Hj(Ci) 19 for each class (Cj) != class(Ci) 20 find k nearest miss item Mj(Cj) 21 end 22 for i from 1 to m do 23 update WF [Ti] 24 end 25 end 26 Selector: 27 begin 28 normalize WR,WF 29 perform feature selection 30 end **31 end**

V. SYSTEM ARCHITECTURE

The system framework combined with three modules. The three modules are feature selection, feature extraction and classification. The goal is to do efficient and accurate forecasting of electricity price.



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FIG 1.SYSTEM ARCHITECTURE

VI. RESULT AND OUTCOME

The result describes forecasting the all the price and predict the final price.FIG 2 describes the dataset selection. The electricity data set can be selected and it is stored in to the database.



FIG 2.DATASET SELECTION



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FIG 3 describes the hybrid feature selection. The features are to be selected from the dataset. Grey correlation analysis (GCA) is used to select the features and remove the redundancy among the features.

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FIG 3: HYBRID FEATURE SELECTION

FIG 4 describes hybrid feature extraction. The features selected by hybrid feature selector can be considered that have no irrelevant features, but also have redundant features. In power price forecasting data requires non-linear mapping to find an appropriate low dimensional value. Kernel Principle Component Analysis (KPCA) uses kernel function to deal with high dimensional and low dimensional data.

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FIG 4: HYBRID FEATURE EXTRACTION



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FIG 5 describes the classification, which can done on the extracted features for accurate price forecasting.

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FIG 5: CLASSIFICATION

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FIG 6 describes the predicted data. The predicted power price is showed from the classification results.

FIG 6: PREDICTED POWER PRICE



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VII. CONCLUSION AND FUTURE WORK

An electricity price forecasting framework, which consists of two-stage feature processing and improved SVM classifier. The end result produces the predicted electricity price. For future work, location based dataset is used. This method using the extracted model instances to find the most two similar regions between two cities by Spatial Distribution. The result will show that the regions are both more consistent with the data in terms of predictive performance.

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