INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

Day-Ahead Electricity Price Predictions in Smart Grids: Leveraging Deep Learning for Smart Forecasting

J. Sunanthini SUNANTHINI@stellamaryscoe.edu.in

Mrs.V.Subitha subitha@stellamaryscoe.edu.in

Mr.C.Bastin Rogers bastinrogers@stellamaryscoe.edu.in

Dr.M.Supriya supriya@stellamaryscoe.edu.in

Mrs.Breethy.S.V breethy@stellamaryscoe.edu.in

Department Of Computer Science Engineering

Stella Mary's College Of Engineering, Tamilnadu, India

Abstract—Power charge estimating is a sizeable piece of the savvy matrix the since it makes shrewd network expense green. All things considered, existing methodologies for expense gauging can be difficult to address with monstrous value information inside the matrix, on the grounds that the overt repetitiveness from trademark decision can't be kept away from and an included framework is moreover needed for organizing the strategies in strength charge determining. To address one of these difficulties, a special power expense anticipating adaptation is created. In particular, 3 modules are coordinated in the proposed model. In the first place, by utilizing converging of Random Forest (RF) and Relief-F calculation, we exhort a half breed work selector fundamentally founded on Gray Correlation Analysis (GCA) to get rid of the capacity overt repetitiveness. Second, a coordination of Kernel element and Principle Component Analysis (KPCA) is used in trademark extraction strategy to understand the dimensionality rebate. At long last, to gauge rate class, we suggest a differential development (DE) based thoroughly Support Vector Machine (SVM) classifier. Our proposed power expense guaging rendition is acknowledged through those three components. Mathematical outcomes show that our thought has progressed generally in execution thin different procedures.

Keywords—Big information; Price forecasting; Classification; Feature selection; Smart gird

1 INTRODUCTION

One of the chief longs for astute framework is to reduce power top burden and to security the distance among energy supply and call for [1]. Clients are equipped for share inside the tasks of smart lattice, wherein the power cost can be diminished by strength upkeep and burden moving. In this model, unique evaluating is a critical mark of clients' exchanging load [1]. For the most part, right component value guaging is expected because of the prerequisite of economy and endeavor [2]. Concerning clients, they're really anxious to perceive whether or not the strength cost surpasses the exact client depicted edges, which they used to decide to turn the heap on or off. Under the present circumstance, clients require the energy charge class. Henceforth, a couple of remarkable edges in view of variable rate estimating calculations are utilized to arrange the power cost. Work estimate strategies are the fundamental of point charge determining calculations, in which the essential method of expense arrangement is imitated by an expense form [3]. Besides, rate class calls for lower precision. Along these lines, strength charge order transforms into a critical need inside the charge determining. The power charge is supported through different elements, for example, gas expense, power necessity, environmentally friendly power supply, etc., and it fluctuates hourly. Since the power rate changes regularly and gigantic amounts of smart meters screen the climate, which incorporates fuel innovation, wind time, and transmission, progressively, how much antiquated data is very enormous [4]-[6].

2 Related works

We assessment the associated works in electricity fee forecasting and characteristic engineering on this element. Machine gaining knowledge of and time-series model are two primary ways for electricity price forecasting. Varshney et al. [7] developed a hybrid version to predict day in advance power market in step with temperature and load facts, with the usage of neural network shape and evaluation of singular spectrum. Mousavian et al. [8] recommend a probabilistic methodology to forecast in step with hour electricity charge, where the bootstrapping era is applied for reading uncertainty and a generalized extreme mastering gadget method is proposed for wavelet neural networks. Kobayashi et al. [9] evolved a switched Markov chain model for solving best electricity pricing problem in realtime

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

based on a welfare function, which considers a tradeoff between customers' utility and strength conservation. Mosbah et al. [10] used multilayer neural networks in composite topology to decorate in keeping with hour strength fee forecasting accuracy. Time series analysis is also extensively utilized in power rate forecasting, in which automobile-regressive integrated transferring average (ARIMA) has good performance in stable power market [11]. Ozozen et al. [11] proposed an ARIMA

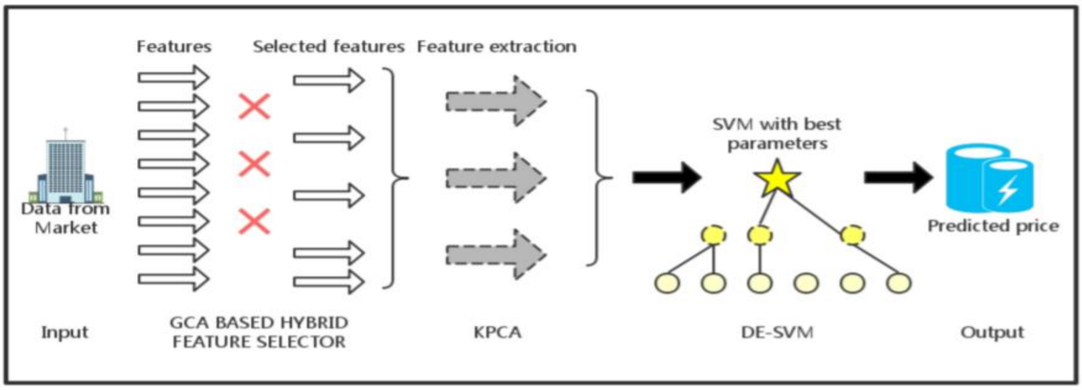

Fig. 1: Our proposed approach

based algorithm to expect power fee in Turkey markets. Because of the lifestyles of numerous outliers in ARIMA, constructing a model with raw facts from marketplace makes the forecasting accuracy risky. Portela et al. [12] evolved a seasonal autoregressive shifting average Hilbertian (AMAH) model to estimate the cell average values in practical time series, which may be carried out to energy fee forecasting.

Feature engineering is fundamental to the utility of classifier. Selection and extraction are not unusual operations in characteristic engineering. In electricity fee, diverse methods are used for feature engineering. Zhao et al. [13] performed a study of current function engineering strategies and mentioned the way to gain suitable features in charge forecasting. Qiu et al. [14] implemented multi-variable mutual facts to function selection. Abedinia et al. [15] extended the Mutual Information (MI) and Interaction Gain (IG) to measure the relevance of capabilities. Qian et al. [16] used C4.5 set of rules for function selection in charge forecasting and the result shows that C4.Five plays higher than Iterative Dichotomiser three (ID3) in choice tree constructing. Mori et al. [17] developed a characteristic extraction set of rules primarily based on Symbolic Aggregation Approximation (SAX) to system time-series records. Previous research in particular cognizance on characteristic choice algorithms or classifiers layout, wherein conventional classifiers, e.G., Decision Tree (DT) and Artificial Neural Network (ANN) are very popular [18], [19]. However, DT typically faces the overfit problem, which means that the DT performs well in education but no longer in prediction [18], and ANN has a constrained generalization functionality and its convergence cannot be effortlessly controlled [20]. Also, these mastering primarily based techniques do no longer take the massive facts into consideration, and the evaluation of overall performance is simplest carried out at the price information, which isn't always pretty large. Hence, the price forecasting accuracy could nonetheless be improved with the assist of large facts.

3 SYSTEM FRAMEWORK

The system framework of HSEC. The modules in this framework are made up with three parts, i.e., feature engineering (feature selection, feature extraction) and classification.

3.1 Design Goals

The goal of our framework is to do efficient and accurate forecasting of electricity price. To achieve this, we need to process the raw data, figure out the selected features and carefully tune the classifier. Thus, the following metrics are important for the processing performance of our proposed framework.

• Accuracy of classification: This is the core goal of our framework design. • Dimensional reduction rate: In this framework, the performance of feature engineering influences the accuracy of classification directly.

• Time-efficiency: Applied in electricity price forecasting, the framework should run fast.

3.2 Framework Overview

The primary issue in electricity price forecasting is accuracy. However, various factors influence the electricity, which makes the classifier training difficult. To

ISSN: 2057-5688

enhance the accuracy of the proposed framework, we develop a parallelized HFS, a KPCA-based feature extraction, and a DE-SVM based classifier. The HSEC begins with standardizing the raw data, which corresponds to the first part in Fig. 1. This standardization process is crucial for the implementation of the whole framework. Secondly, data flow into the GCA based HFS, where data will be used to train Relief-F and RF in parallel. This feature selector decides whether a feature is reserved by an index which is given by Relief-F and RF and is called feature importance. Due to the decoupling design of this selection algorithm, this process could execute distributively. Thirdly, KPCA will be performed in the selected features for further removal of redundant features. In our proposed framework, factors incorporate depending on feature importance and redundancy. For example, the weather condition may affect the generation of solar and wind energy, this constrain will be reflected in the redundancy among weather, solar, and wind. Finally, the processed data is sent to build SVM. Since SVM is controlled by several super parameters, we use DE algorithm to tune these parameters.

4 GCA BASED HYBRID FEATURE SELECTOR

This section describes the process of features selection. We propose a new parallel HFS based on GCA by fusing RF and Relief-F, and it is controlled by a new proposed threshold μ. The fusion of RF and Relief-F brings a feature selection that is more accurate. The Relief-F and RF can give feature importance, respectively. These two approaches are both efficient. Features are first roughly selected by GCA, and the HFS performs the further selection by μ. We assume a matrix

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

------------- (1)

to denote the electricity price data. The rows represent the time stamps and columns denote the feature index, i.e., aij is the j-th component of the data that i hour ahead of the price that is to be predicted. The matrix can be also formulated as

$$A = \begin{bmatrix} \vec{t_1} \\ \vec{t_2} \\ \vdots \\ \vec{t_m} \end{bmatrix}$$ -------(2)

Where,

$$\vec{t_k} = [a_{k1}, a_{k2}, \ldots, a_{kn}] \qquad k \in [1, m].$$ ---------(3)

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

4.1 Preliminaries: Grey Correlation Analysis

Since various features have various degrees of influence on the final predicted electricity price, we use GCA to determine the importance of each feature. GCA calculates the correlation between each feature and the final electricity price. Via GCA, the depth of RF could be effectively controlled. In principle, GCA determines the correlation by quantifying the degree of" closeness" between two different data sequences. The closer two data sequence are, the greater correlation is. Thus, GCA can provide a quantitative measure of the closeness between the electricity prices. Since the physical meaning of each feature in the framework is different, the dimension of data is not necessarily the same. Therefore, when the grey correlation grade analysis is carried out, the non-dimensional data processing will be executed accordingly.

$$\lambda_i^*(k) = \frac{\lambda_i(k) - min\lambda_i(k)}{max\lambda_i(k) - min\lambda_i(k)} \quad \text{------(4)}$$

Algorithm 1: Hybrid Feature Selector

Input: $W^R[T_k] \leftarrow 0.0, W^F[T_k] \leftarrow 0.0, A[], R[n]$
Output: $W^R[T_k], W^F[T_k]$

begin
  initialization: set all weight $W^R[T_k] \leftarrow W^F[T_k] \leftarrow 0.0$, read data from $A[]$
  Evaluator ς:
  begin
    for k *from* 1 *to* m **do**
      for i *from* 1 *to* n **do**
        calculate $errOBB1_i$ using corresponding OBB data set of decision tree[i]
        randomly add noise to all OBB data on feature T_k
        calculate $errOBB2_i$ using corresponding OBB data set of decision tree[i]
      end
      calculate the importance of feature $W^R[T_k] \leftarrow \frac{\sum_{i=1}^{n}(errOBB2_i - errOBB1_i)}{n}$
    end
  end
  Evaluator τ:
  begin
    for k *from* 1 *to* m **do**
      select an item in $class(C_i)$ by random
      find k nearest hits item $H_j(C_i)$
      for each $class(C_j) \neq class(C_i)$
      find k nearest miss item $M_j(C_j)$
    end
    for i *from* 1 *to* m **do**
      update $W^F[T_i]$
    end
  end
  Selector:
  begin
    normalize W^R, W^F
    perform feature selection
  end
end

Algorithm 2: Differential Evolution-based SVM

Input: $X_i \leftarrow (0,0,0)$
Output: $F(y) = \{C_1, C_2, ..., C_k\}$

begin
  set g_{max}, F, CR, Np,
  randomly set $X_i \leftarrow \{c, \sigma, \varepsilon\}, i \in [1, Np]$
  for i *from* 1 *to* Np **do**
    $f_i(X_i) \leftarrow \frac{1}{TN}\sum_{i=1}^{T} N(\tilde{y}_i - y_i)^2$
    if $f_i(X_i) < f_{i+1}(X_{i+1})$ **then**
      reserve $f_i(X_i)$
      compare $f_i(X_i)$ with $f_{i+2}(X_{i+2})$
    else
      reserve $f_{i+1}(X_{i+1})$
      compare $f_{i+1}(X_{i+1})$ with $f_{i+2}(X_{i+2})$
    end
    obtain $f_{min}(X_i)$ and denote the X_i as X_*
  end
  $V_i^{g+1} \leftarrow X_*^g + F(X_{r1}^g - X_{r2}^g), u_{i,j}, X_i^{g+1}$
  $X_* \leftarrow (c_*, \sigma_*, \varepsilon_*)$
  solve classification function, output $F(y)$
end

5 CLASSIFIER ADJUSTMENT

After the two-stage feature selection and extraction, unimportant and redundant features have been dropped. This section describes our proposed approach that accomplishes the final electricity price forecasting via the processed data. Since SVM is robust and efficient enough in electricity price data, we choose SVM as

ISSN: 2057-5688

the classifier. In this section, the formulated classification problem are investigated first. After that, the DE based SVM is proposed to optimize this problem.

As previously discussed, our goal is to minimize the regularized risk function. However, there is a strong relationship between the regularized risk function of SVM and the value of super parameters, which are c (cost penalty), ε (insensitive loss function parameter) and σ (kernel parameter). However, how to tune these three basic super parameters for higher accuracy and more efficiency is still a critical issue. The basic method used to adjust super parameters of SVM is gradient descent (GD) algorithm or cross validation [20]. However, these two methods bring much computational complexity and may be unable to converge. In HSEC, therefore, a reliable Differential Evolution (DE) algorithm is applied to tune the super parameters. In essence, DE mainly consisting of four procedures to optimize the target, which are initialization, crossover, mutation and selection of the super parameters. Every different vector consists of the values of these super parameters can be a component in the population. The current population, represented by Pc, consists of D-dimensional vectors

$$X_i^g = \{X_1^g, X_2^g, ..., X_D^g\}, i \in [1, N_p] \quad ....5$$

According to the integration of HFS, KPCA and DESVM, our electricity price forecasting framework can predict the electricity price accurately. In the next section, we will give experiments and analysis based on the real-world price data.

6. SIMULATION RESULTS

GCA based HFS is applied to roughly select features form hourly electricity price data during 2010-1-1 to 2015- 12-31 in ISO NE-CA. In feature selection, every feature sequence has a form as a vector. The components of this sequence represent the feature values in different timestamps. Since our goal is to predict the electricity price, which is named regulation clearing price (RegCP) in the data, features that have little effect on the price can be removed. Before HFS, GCA performs the correlation calculation between features and RegCP. The grey correlation grade indicates that most features' grade is above 0.5. We drop four features with obvious low grade, i.e., features DA-CC (0.8543), RT-CC (NaN), REFUSE (0.2341), and OTHER (0.3049). According to the results generated by GCA, the feature importance of reserved features can be evaluated. We perform Evaluator ς and τ, described in Algorithm 1, to obtain the importance value of each feature. where negative values mean that the sum of diff() among nearest hits items is larger than that among the nearest miss items. In order to boost the DE-SVM classifier, we discuss the different values of threshold μ, which controls the feature selection. For example, updating μ results in the dropping of DEMAND. With the increase of threshold μ, more features are dropped, resulting in the increase of training speed and the decrease of accuracy.

In order to investigate the capability of HSEC, comparisons among different benchmarks are conducted in this part. The benchmarks used in this part. The HSEC has higher accuracy in electricity price forecasting than all the benchmarks. The comparison among frameworks A, B, C and HSEC spots that every module in our proposal can improve the accuracy of electricity price forecasting. The HSEC reduces the irrelevance and redundancy among features, and uses DE to tune the super parameters of SVM, which guarantees the accuracy of electricity price forecasting.

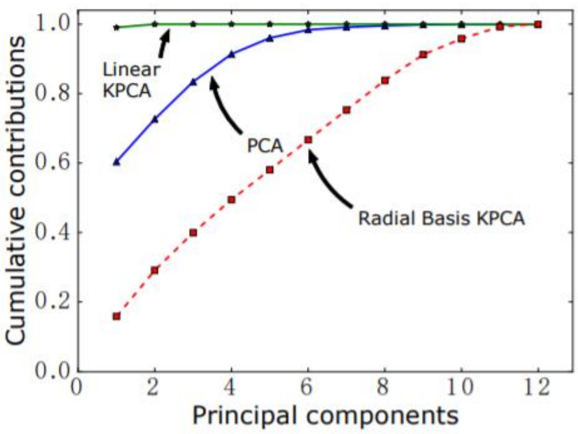

Fig. 1: Performance of PCA, linear KPCA and radial basis KPCA on features.

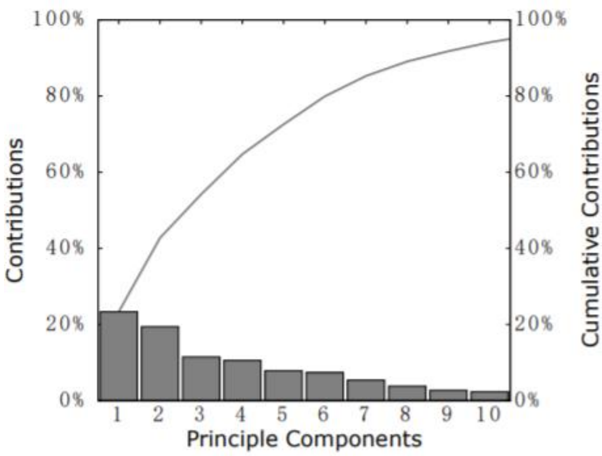

Fig. 2: Cumulative contribution of radial basis KPCA

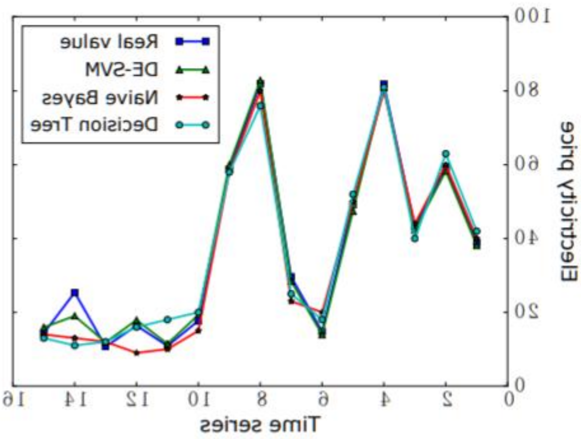

Fig. 3: Comparison on price forecasting among Naive Bayes, Decision Tree and DE-SVM

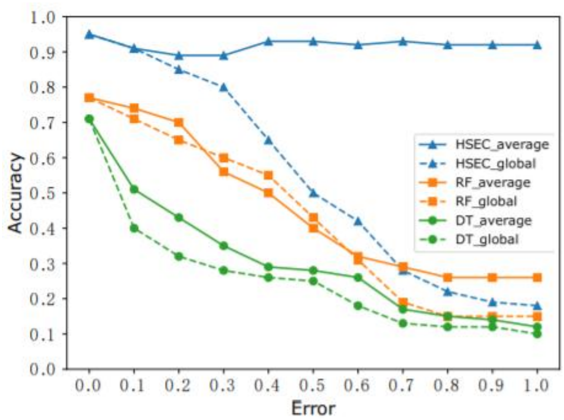

Fig. 4: Comparison on robustness among HSEC and benchmark frameworks

7. CONCLUSIONS AND FUTURE WORK

In this paper, we've explored the power charge anticipating inconvenience in astute matrix through joint thought of capacity designing and classifier boundaries change. An energy value estimating system which comprises of two-levels work handling and advanced SVM classifier has been proposed to tackle this issue. In particular, to choose those significant abilities, a spic and span mixture trademark selector in light of GCA is utilized to way the n-layered time arrangement as an info. Moreover, KPCA is executed to extricate new abilities with less overt repetitiveness, which improves SVM classifier in exactness and speed. Also, the DE calculation gets the best striking boundaries for DESVM regularly and really. The mathematical outcomes have shown that our proposed system is more prominent right than various benchmark calculations. With the thought of the huge measures of insights, it's miles huge for our system to satisfactorily utilize calculation sources and backing the equal figuring. Not quite the same as customary power value determining techniques in which the date is handled successively, the proposed structure is not difficult to place into impact on a parallelized and apportioned framework. Later on, the real time prerequisite might be thought about in this system.

REFERENCES

ISSN: 2057-5688

[1] X. Chen, Y. Zhou, W. Duan, J. Tang, and Y. Guo, "Design of intelligent Demand Side Management system respond to varieties of factors," in Proceedings of China International Conference on Electricity Distribution (CICED), 2010, pp. 1-5.

[2] A. H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," IEEE Transactions on Smart Grid, Vol. 1, No. 2, 2010, pp. 120-133.

[3] M. Erol-Kantarci and H. T. Mouftah, "Energy-efficient information and communication infrastructures in the smart grid: a survey on interactions and open issues," IEEE Communications Surveys and Tutorials, Vol. 17, No. 1, 2015, pp. 179-197.

[4] K. Wang, H. Li, Y. Feng, and G. Tian, "Big data analytics for system stability evaluation strategy in the energy internet," IEEE Transactions on Industrial Informatics, Vol. PP, No. 99, Apr. 2017, pp. 1-1.

[5] ISO New England Energy Offer Data [Online]. Available: www.iso-ne.com/isoexpress/web/reports/pricing/-/tree/dayahead-energy-offer-data, 2016.

[6] K. Wang, Z. Ouyang, R. Krishnan, L. Shu, and L. He, "A game theory based energy management system using price elasticity for smart grids," IEEE Transactions on Industrial Informatics, Vol. 11, No. 6, Dec. 2015, pp. 1607-1616.

[7] H. Varshney, A. Sharma, and R. Kumar, "A hybrid approach to price forecasting incorporating exogenous variables for a day ahead electricity Market," IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, 2016, pp. 1-6.

[8] M. Rafiei, T. Niknam, and M. H. Khooban, "Probabilistic forecasting of hourly electricity price by generalization of elm for usage in improved wavelet neural network," IEEE Transactions on Industrial Informatics, Vol. 13, No. 1, Feb. 2017, pp. 71-79.

[9] K. Kobayashi, "Optimal real-time pricing of electricity based on switched markov chain models and welfare maximization," IEEE 4th International Conference on Cyber-Physical Systems, Networks, and Applications (CPSNA), Nagoya, 2016, pp. 35-39.

[10] H. Mosbah and M. El-hawary, "Hourly electricity price forecasting for the next month using multilayer neural network," Canadian Journal of Electrical and Computer Engineering, Vol. 39, No. 4, Fall 2016, pp. 283-291.

[11] A. Ozozen, G. Kayakutlu, M. Ketterer, and O. Kayalica, "A combined seasonal ARIMA and ANN model for improved results in electricity spot price forecasting: case study in Turkey," Portland International Conference on Management of Engineering and Technology (PICMET), Sept. 2016, pp. 2681-2690.

[12] J. Portela, A. Munoz, and E. Alonso, "Forecasting functional time series with a new Hilbertian ARMAX model: application to electricity price forecasting," IEEE Transactions on Power Systems, Vol.PP, No.99, 2017, pp.1-1.

[13] J. H. Zhao, Z. Y. Dong, and X. Li, "Electricity price forecasting with effective feature

preprocessing," in Proceedings of IEEE Power Engineering Society General Meeting, 2006, pp. 8.

[14] Z. W. Qiu, "Mutivariable mutual information based feature selection for electricity price forecasting," in Proceedings of International Conference on Machine Learning and Cybernetics, 2012, pp. 168-173.

[15] O. Abedinia, N. Amjady, and H. Zareipour, "A new feature selection technique for load and price forecast of electrical power systems," IEEE Transactions on Power Systems, 2016, DOI: 10.1109/TPWRS.2016.2556620.

[16] H. Qian and Z. Qiu, "Feature selection using C4.5 algorithm for electricity price prediction," in Proceedings of International Conference on Machine Learning and Cybernetics, 2014, pp. 175-180.

[17] H. Mori and Y. Umezawa, "A SAX-based method for extracting features of electricity price in power markets," in Proceedings of Transmission and Distribution Conference and Exposition: Asia and Pacific, 2009, pp. 1-4.

[18] K. Wang, J. Yu, Y. Yu, Y. Qian, D. Zeng, S. Guo, Y. Xiang, and J. Wu, "A survey on energy internet: architecture, approach and emerging technologies," IEEE Systems Journal, Vol. PP, No. 99, Jan. 2017, pp. 1-1.

[19] H. Jiang, K. Wang, Y. Wang, M. Gao, and Y. Zhang, "Energy big data: a survey," IEEE Access, Vol. 4, Aug. 2016, pp. 3844-3861.

[20] A. Shiri, M. Afshar, A. Rahimi-Kian, and B. Maham, "Electricity price forecasting using Support Vector Machines by considering oil and natural gas price impacts," in Proceedings of IEEE International Conference on Smart Energy Grid Engineering (SEGE), 2015, pp. 1-5.