Journal of Energy and Economic Development,
Niroo Research Institute.
Vol. 1, Issue. 1, Summer 2022 , Pages 22-33
Journal homepage: http:// jeedev.nri.ac.ir

Data Mining Techniques in Efficiency Analysis of Wholesale Electricity Market: A Case Study of Iran

Masoumeh Rostam Niakan Kalhori[1*], Iman Taheri Emami[2], Masoud Hasani Marzooni[3]

1 Assistant Professor, Department of Energy Economics, Niroo Research Institute, Iran,

2 Ph.D. Candidate, Department of Electrical Engineering, Amirkabir University of Technology, Iran,

3 Assistant Professor, Department of Energy Economics, Niroo research institute, Iran

Abstract. In this paper, predictive data mining models are employed to get insights into the efficiency of a deregulated electricity market. The bidding data of Iranian generation units in a two-phase approach are classified. Firstly, common factors that could contribute to investigating the efficiency of generation units' bidding behavior are identified by feature selection algorithms. Then, classification rule mining algorithms are applied to extract if-then rules related to bidding blocks of generation units. The three most-applicable algorithms for classification rule mining are compared statistically. The two first algorithms are decision trees based on a direct approach. Finally, the third algorithm is the sequential covering method, perceived as an indirect approach to classification rule mining. The extracted rules are of significant importance for wholesale electricity market monitoring units (MMUs) to evaluate the market and its players thoroughly. The experimental results indicate that the partial decision tree outperforms other investigated methods.

Keywords: *Deregulated Electricity Markets, Market Monitoring, Data Mining, Machine Learning, Classification Rule Mining.*

INTRODUCTION

In the past two decades, the power industry became the target of market discipline throughout the world. Regulators and policymakers need in-depth knowledge about the market dynamics and bidding behavior of market players to devise an effective market design that balances market participants' interests and promotes both short- and long-term efficiencies. Accordingly, Market Monitoring Units (MMUs) play a vital role in the restructured environment. It should be noted that emerging electricity markets generate a large volume of data. This includes bids from suppliers, the power consumption of demands, and the physical constraints of the power system. In this situation, data mining (DM) techniques are employed by MMUs to analyze the vast amount of electricity market data to extract knowledge about the market dynamics and bidding behavior of market participants.

[*] Corresponding author at Energy economics department, Niroo Research Institute, Tehran, Iran, Tel.: +98 88079400; fax: +98 2188078296. Address: Niroo Research Institute, At the End of Shahid Dadman Blv. Shahrak Ghods, TEHRAN, IRAN.
E-mail addresses: Mniakan@nri.ac.ir (M. Rostam Niakan Kalhori), i.thri@aut.ac.ir (I. Taheri Emami), mhasani@nri.ac.ir (M. Hasani Marzooni)
https://doi.org/10.30503/jeedev.2022.278926.1010

The applications of DM techniques in electricity market monitoring have been widely addressed in the literature. These applications range from market power assessment to demand-side management (DSM), congestion management through long-term price, demand forecast, and network expansion decisions. The efficiency of a centralized market depends on the level of competition that exists in it (Taheri et al., 2022). In a market with perfect competition, none of the participants has the power to influence the market price. Accordingly, various methods have been examined by MMUs to detect the market power in the wholesale electricity markets (Emami et al., 2020; Taheri et al., 2013).

In the following, we introduce some studies that used DM techniques to assess the competitiveness of GENCOs or the market as a whole (Chernenko, 2015; Rostamnia & Rashid, 2019; Zamani-Dehkordi et al., 2015). In (Zamani-Dehkordi et al., 2015), an anomaly detection algorithm, combining proximity-based, regression, and extreme value models has been employed to identify anti-competitive bids. A price forecasting model to evaluate the competitiveness of the electricity market, is presented in (Rostamnia & Rashid, 2019). In order to develop the model, a multi-layer perception was employed via back propagation utilizing Levenberg-Marquardt mechanism. In (Chernenko, 2015) a time series autoregressive model to assess long-run and short-run actual market power levels in the liberalized Russian electricity market has been designed. In some studies, DSM has been used as a promising way of increasing electricity market efficiency (Spees & Lave, 2007). So, some papers applied DM techniques in DSM (Huang et al., 2012; Shao et al., 2020; Zareipour et al., 2010). In (Huang et al., 2012; Zareipour et al., 2010), several DM approaches have been examined to classify electricity prices for DSM, applying in New York, Ontario, and Alberta electricity market prices. A price classification framework for DSM has been proposed in (Shao et al., 2020). The proposed framework consists of a Bayesian extreme learning machine model, minimum redundancy maximum relevance algorithm, and multivariate sequence segmentation. The proposed approach has been evaluated using hourly clearing price cases from Canada's Ontario to New York electricity markets.

Transmission congestion provides some opportunities for the exercise of market power (Narain et al., 2020). Therefore, accurate congestion forecasting helps the market operators to manage transmission lines' congestion. Some papers developed DM-based methods to predict congestion in transmission networks (Sánchez-Úbeda et al., 2001; Staudt et al., 2019). In (Sánchez-Úbeda et al., 2001), a DM-based methodology has been proposed to identify possible congested transmission lines. In (Staudt et al., 2019) an artificial neural network-based congestion forecasting model is proposed. In (Staudt et al., 2019), only publicly available day-ahead data are used as input to the congestion forecasting model. The absence of correlation between price increments over any time scale is a basic feature of electricity market efficiency (Jose Alvarez-Ramirez & Escarela-Perez, 2010; J Alvarez-Ramirez et al., 2009). Accordingly, (Jose Alvarez-Ramirez & Escarela-Perez, 2010; J Alvarez-Ramirez et al., 2009) proposed a DM-based methodology to quantify time-dependent correlations of electricity market prices/variables. Also, the authors of (J Alvarez-Ramirez et al., 2009) applied the proposed approach to investigate correlations between the demand and price time series in the Australian electricity market. In the restructured environment, regulators and policymakers need long-term price and congestion forecasts to plan future investments and network expansion (Bemš et al., 2016; Chicco et al., 2019; Ferreira et al., 2011; Peco et al., 1999; Saez et al., 2019; Van den Bergh et al., 2016). Accordingly, researchers and MMUs use different DM techniques to predict long-term electricity prices and possible congested lines (Ferreira et al., 2011; Peco et al., 1999). Two-step and K-means clustering algorithms were used in (Ferreira et al., 2011) to extract the knowledge for supporting the ISO with network expansion planning. To evaluate the proposed DM-based methodology, (Ferreira et al., 2011) used an LMP database from the CAISO in 2009. In (Peco et al., 1999), decision tree methods have been utilized to determine the optimal transmission expansion planning. Transmission constraints fragment the European electricity market into smaller zones, where cross-zonal exchanges are restricted according to available transfer capacities (Bemš et al., 2016). Accordingly, a well-planned bidding zone configuration plays a key role in the efficiency of the

European electricity market. Ref (Chicco et al., 2019) devised different clustering algorithms to design bidding zones for the European electricity market. On the other hand, market fragmentation creates market power and consequently decreases market efficiency. Accordingly, the European Union is immersed in an integration process to build a unified electricity market. In the process of European electricity market integration, the Flow-Based Market Coupling (FBMC) approach has been implemented to manage cross-border capacity allocation (Van den Bergh et al., 2016). In (Saez et al., 2019), the price convergence across the Central Western Europe Region has been analyzed to assess the effectiveness of the FBMC approach. For this purpose, different machine learning models have been developed in (Saez et al., 2019) to build robust predictive models that policymakers can use to detect congestion patterns.

According to the microeconomic theory, competition leads the wholesale electricity market toward efficient outcomes (Cramton, 2004). Under the competitive electricity market, GENCOs seek to adopt an optimal bidding strategy to gain maximum profit. Therefore, market regulators expect and encourage profit maximization. Hence, assessing the optimality of GENCOs' bidding behavior is considered a crucial issue for MMUs. On the other hand, (Yousefi et al., 2017) proved that the optimum strategy should exercise the right of a GENCO to submit a bid with the maximum allowable quantity-price pairs/steps.

There is currently a gap in the literature on using DM techniques to assess the efficiency of power markets. According to the aforementioned descriptions, this paper examines the efficiency of the Iranian wholesale electricity market (IWEM) in 2016. It is worth mentioning that IWEM is ruled under the Pay as Bid (PaB) pricing mechanism. Due to the nature of the PaB pricing mechanism, adopting optimal bids has significant effects on the profit of generating units in IWEM. To fulfill this aim, machine learning is employed as a subset of DM techniques. That is to evaluate the optimality of generating units' bidding behavior by analyzing the number of bid steps.

So, the main contributions of this paper are summarized as follows:

Firstly, multiple feature selection algorithms are applied to identify the main factors influencing the number of generation units' bidding blocks.

Moreover, three classification rule-mining algorithms are compared to extract if-then rules providing descriptive knowledge about Iran's electricity market. The most precise algorithm is found using two evaluation criteria: accuracy and F-measure. The if-part of these rules includes features of generation units, and the then part classifies them based on their number of bidding blocks into low, medium, and high blocks.

The rest of the paper's organization is as follows: Section 1 represents the main characteristics of the Iranian wholesale electricity market. Methodology and experimental results are described in sections 2 and 3, respectively. Finally, conclusions are drawn in section 4.

1. OVERVIEW OF THE IRANIAN WHOLESALE ELECTRICITY MARKET

The Iranian wholesale electricity market (IWEM) was established in 2003. Market operators, sellers, and buyers are three major participants in IWEM (Yousefi et al., 2017). Iran Grid Management Company (IGMC) is responsible for operating IWEM. Regional electric companies (RECs), regional water companies (MMI), thermal power plants holding companies (MBH), private power plants (ZPC), power plants funded by the government and private sector together (C27), and power plants under the management of the Ministry of Energy (SUP) act as sellers (Yousefi et al., 2017). It is noteworthy to note that RECs have a managing role in their geographical area.

On the other hand, distribution companies (DISCOs), RECs, and independent consumers act as buyers. Currently, the IWEM is a pool-based day-ahead market. The IGMC runs a single-sided day-ahead price-discriminatory auction to purchase the electricity on behalf of buyers (Nazemi &

Mashayekhi, 2015). All generating units in the market are mandated to participate in wholesale electricity auctions daily. The generation units submit their bids to the IGMC hourly. In the IWEM, each bid is a multi-step price-quantity supply curve with up to 10 steps. A pre-determined price cap is imposed on generator unit bids. Buyers predict the demand for each hour and submit their estimations to the IGMC. The IGMC solves the SCUC problem to clear the IWEM. The objective of SCUC is to minimize the total cost of energy procurement with consideration of Iran's grid constraints (Asgari & Monsef, 2010). Besides, the day-ahead wholesale electricity market in Iran is based on the pay-as-bid.

2. METHODOLOGY

Aiming at extracting If-Then rules to gain insights into the origins of the strategic bidding behavior of generation units, this paper uses classification rule mining as a class of machine learning methods. Since, in this paper, the output variable is categorical, classification rule mining has been selected as the primary approach to rule generation. As a two-step process, data classification includes the learning step (constructing model) and classification step (predicting class label for the test or unseen data). In the learning (training) step, a classifier is built by learning a model from training data, including tuples and their associated class labels. A tuple, *X*, is an n-dimensional vector $X=(x_1, x_2, \ldots, x_n)$ labeled by an output class *Y* that is discrete-valued and unordered as a categorical attribute. It is categorical (or nominal) in that each value serves as a category or class. The second step includes determining the output class of test or unseen data using the first step model.

Two main approaches to classification rule mining are named direct and indirect:

- Indirect approach: as the name implies, in the indirect process, at the first step, classification is implemented by a machine learning method, and then the results of the classifier are represented in the form of rules. One of the most popular indirect approaches to If-Then rule extraction is decision tree classification. The decision tree is a graphical structure consisting of linked nodes and leaves. In the learning process, a decision tree is constructed by creating branches based on the input features. Representing classification rules by decision tree helps them to make more sense and be easier to understand, especially in the case of large decision trees. "To extract rules from a decision tree, one rule is created for each path from the root to a leaf node. Each splitting criterion along a given path is logically ANDed to form the rule antecedent ("IF" part). The leaf node holds the class prediction, forming the rule consequent ("THEN" part)" (Han et al., 2006).

The first work of decision tree induction traces back to the ID3 (Iterative Dichotomiser) introduced by J. Ross Quinlan (J. Ross Quinlan, 1986). Quinlan later presented C4.5 (a successor to ID3) (J Ross Quinlan, 2014) based on a greedy process constructing a decision tree in a top-down recursive divide-and-conquer approach.

The general iterative algorithm of constructing a decision tree is as follows:

- The process of constructing the tree starts with a single node, *N*, representing the training tuples in D (a data partition. Initially, the training data set).
- The node *N* is selected as a leaf labeled by a class if all tuples in *D* are all of the same class. Otherwise, based on a splitting rule *(*a heuristic procedure for selecting the attribute that "best" discriminates the given tuples according to the class) the splitting criterion is chosen. This criterion indicates the attribute that the branches of the node *N* would be grown based on.
- The results of the splitting criterion bring about growing branches from node *N*, and partitioning tuples in *D*. For a discrete-valued splitting attribute *A* with distinct

values$a_1, a_2, \dots, a_v$, a branch is formed for each $a_j; j = 1,2, \dots, v$; and D is partitioned into subsets based on these values. In the case of a continuous-valued splitting attribute, the branches are grown based on a splitting point.

- In a recursive process, the tree is constructed for the partitions of *D*. The algorithm uses the same process recursively to form a decision tree for the tuples
- The recursive partitioning continues until one of the following terminating conditions is satisfied:

1. Partition *D* (represented at node *N*) includes tuples with the same output class.
2. There are no remaining attributes on which, the tuples may be further partitioned.
3. There are no tuples for a given branch.

The algorithm of the splitting rule is of critical importance to developing a decision tree. Information gain (J Ross Quinlan, 2014) is the first algorithm used in ID3 in which the selected splitting attribute of node *N* contains the highest information gain minimizes the information required for classifying the tuples in the resulting partitions.

"The information gain measure is biased toward tests with many outcomes. That is, it prefers to select attributes having a large number of values". In C4.5, this problem of ID3 has been addressed by normalizing the information gain, defining a "split information" value for each attribute A.

$$\alpha_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2\left(\frac{|D_j|}{|D|}\right) \qquad (1)$$

The split information, $\alpha_A(D)$, represents how much information is generated by splitting the training data set, *D*, into *v* partitions. These partitions correspond to the *v* outcomes of a test on attribute *A*. The gain ratio is defined as follows:

$$Gainration(A) = \frac{\text{Gain }(A)}{\alpha_A(D)} \qquad (2)$$

In (2), Gain ratio (*A*) is the gain ratio of attribute A, and Gain (*A*) (the output of the "information gain" method) displays the information that would be gained by branching on *A*. The attribute with the maximum gain ratio is selected as the splitting attribute.

In this paper, one of the comparing methods used to find the IF-Then rules is C4.5 named J48 in the Weka software.

After building a tree, anomalies in the training data might emerge in the branches as a result of noise or outliers. This problem, which is referred to as overfitting tree, can be dealt with by implementing pruning methods to eliminate the unnecessary branches. As a result, the pruned trees will be less complicated and faster to classify.

In C4.5, an unpruned decision tree is firstly transformed into a set of rules generated for each path from the root to a leaf. Then, pruning is implemented in a greedy algorithm. In (Frank & Witten, 1998), an algorithm named partial decision tree is proposed as a solution to this complex optimization problem. In this algorithm, two main phases of C4.5, construction and pruning, are integrated to find a stable subtree that can be simplified no further. "To explain it briefly, in a partial decision tree to construct a single rule a pruned decision tree is built for the current set of instances, the leaf with the largest coverage is made into a rule, and the tree is discarded (Frank & Witten, 1998)". Therefore, the partial decision tree, named PART in the Weka, is the second indirect method of classification rule mining used in this paper.

- Direct approach: In this approach, the If-Then rules are extracted directly from the training data by learning sequentially, and each rule covers as many as possible tuples of each output class. In this paper the RIPPER, a well-known sequential covering method, is used to compare two direct and indirect approaches.

The general strategy consists of learning rules one at a time. After learning a rule, the tuples covered by it are eliminated and the process is repeated for the remaining tuples. This approach differs from decision trees in terms of the fact that in the decision tree's learning process a set of rules are learned simultaneously.

RIPPER, named JRip in Weka, is the third classification rule mining method used in this paper to generate IF-Then rules.

There is a risk of overfitting in a large tree that may not be generalizable enough. On the other hand, it should not be quietly small and unable to capture the information hidden in samples completely. Pruning is the process of setting up the size of a tree suitably by removing nodes without informative data. They have been designed to reduce the complexity of tree structure while ensuring that the classification accuracy is not decreased. Reduced Error Pruning (REP) is a post-pruning method to find the smallest version of the most accurate subtree with respect to the pruning set (J. Ross Quinlan, 1987).

Starting with the complete tree T_{max}, and for each internal node *t* of T_{max} REP compares the number of classification errors made on the pruning set when the subtree T_t is kept, with the number of classification errors made when *t* is turned into a leaf and associated with the most appropriate class. Sometimes, the simplified tree has a better performance than the original one. In this case, it is advisable to prune T_t. This branch pruning operation is repeated on the simplified tree until further pruning increases the misclassification rate (Esposito et al., 1997).

In this paper, REP is used for tree pruning in comparison to the other three methods: J48, PART, and JRip. The experimental framework will be represented in the next section.

3. EXPERIMENTAL FRAMEWORK

All experiments have been implemented in WEKA, a robust data mining software, including various machine-learning algorithms based on Java.

3.1 Feature Selection

During the feature selection process, the parameters affecting the output are determined to eliminate redundant and irrelevant ones. The input and output from the available database are as follows.

The number of bidding blocks of generation units is the output of the classifier. The bidding blocks range is discretized into three intervals, i.e. low (1<blocks<3), medium (4<blocks<7), and high (8<blocks<10). Moreover, seven attributes, namely rgn, tech, own, ctorm, ctorrm, avc, and ngu are inputs to the classifier. These features are introduced in Table 1. It is worth mentioning that generation units are located in eight different regions of Iran.

Table 1. ATTRIBUTES, DESCRIPTION AND THEIR POSSIBLE VALUES

Attr.	Description	Possible Values
rgn	Region ID	1 to 8
tech	Generation technology	1 (steam), 2 (gas), 3 (combined cycle), 4 (hydro), 5 (DG), 6 (nuclear)
own	Ownership	1 (REC), 2 (MMI), 3 (MBH), 4 (ZPC), 5 (C27), 6 (SUP)
ctorm	$\text{ctorm} = \frac{\text{unit capacity}}{\text{RM}^1}$	0 < ctorm < 1
ctorrm	$\text{ctorrm} = \frac{\text{unit capacity}}{\text{RRM}^2}$	$-\infty$ < ctorrm < ∞
avc	The average variable cost of the generation unit	0 < avc < 440000
ngu	Number of generation units housed in PP	1 (ngu<4), 2 (ngu>3)

[1]RM represents system reserve margin, RM=total generation capacity-total demand.

[2]RRM represents regional reserve margin, RRM=total regional generation capacity-total regional demand.

These electric regions are connected to their neighbors via tie lines. Additionally, generation units are categorized into steam, gas, combined cycle, hydroelectric, DGs, and nuclear in terms of different primary energy resources. Both ctorm and ctorrm are continuous variables. The ngu feature is discretized into two intervals, i.e. ngu<4 and ngu>3, and then these intervals are mapped to consecutive positive integers 1 and 2, respectively. It should be noted that one or more generation units might be housed in one power plant (PP).

Two approaches, Wrapper, and correlation-based evaluation have been applied to select compelling features. The main idea of the wrapper method is to consider the induction algorithm as a black box. “The induction algorithm is run on the dataset, usually partitioned into internal training and holdout sets with different sets of features removed from the data. The feature subset with the highest evaluation is chosen as the final set on which to run the induction algorithm” (Kohavi & John, 1997). In the correlation-based method, the value (merit) of different subsets of features is assessed regarding their forecasting ability. Two criteria, maximum correlation between features and output and minimum intra-correlation among features, are considered in the evaluation. The results of feature selection methods are represented in Table 2. Based on this table all input features are of considerable importance in the classification of the output feature though they experience different ranks. It should be noted that the tuned parameters of the decision tree methods applied in the feature selection are represented in the fourth column of Table 2.

Table 2. FEATURE SELECTION RESULTS

Feature selection method	Search method	Learning method for evaluation	Results
Wrapper	Best first	Decision tree (J48)	**Selected attributes:** Location; Technology; Unit cap; Unit num; Load; Saving; Avc.
Wrapper	Best first	Decision tree (J48)	**Selected attributes:** Owner type; Location Technology; Unit cap; Unit num ; Load; Saving; Avc.
Wrapper	Greedy stepwise	Decision tree (J48)	**Ranked attributes:** 8 Avc**;** 4 Unit cap**;** 2 Location**;** 7 Saving**;** 3 Technology**;** 6 Load**;** 5 Unit num**;** 1 Owner type.
Wrapper	Greedy stepwise		**Ranked attributes:** 8 Avc; 2 Location**;** 4 Unit cap**;** 7 Saving**;** 3 Technology**;** 5 Unit num**;** 6 Load**;** 1 Owner type **Selected attributes:** 8,2,4,7,3,5,6,1 : 8
Correlation	Greedy Stepwise		**Ranked attributes:** 8 Avc**;** 1 Owner type; 4 Unit cap**;** 5 Unit num**;** 3 Technology**;** 2 Location**;** 7 Saving; 6 Load **Selected attributes:** 8,1,4,5,3,2,7,6 : 8

3.2 Train and Test Sets

One of the most significant aspects of a machine learning method is its generalization strength. Meaning, to what extent could this method correctly forecast the output of the data from which it has learned. Two approaches are commonly applied to split a data set to training and testing parts. A simple rule of thumb is to use something around a 70:30 to 80:20 training: testing split. Besides, k-fold cross-validation is another approach in which the data set is partitioned into k subsets named folds. The model is trained by k-1 folds and validated by the remaining fold playing the role of a testing set. The performance measure reported by k-fold cross-validation is calculated as the average of the values computed in k iterations.

Although cross-validation is time-consuming, it seems to be more reliable as the model is trained by various subsets of the data to maintain robustness. Although in this paper learning has been done by both approaches, the results of 10-fold cross-validation are reported because it has brought more accurate results.

3.3 Performance Evaluation Criteria

Here, two classification performance measures are used to analyze the comparing methods.

3.3.1 Performance measures

To evaluate the results of the applied classification rule mining methods, two criteria are used: accuracy and F-measure.

Accuracy: as a criterion displaying the percentage of correctly classified test data, Accuracy is of significant importance in evaluating a classification model.

F-measure: it is a criterion integrating four outputs of a confusion matrix: FN (False Negative), FP (False Positive), TN (True Negative), and TP (True Positive). This criterion determines the cost of false forecasting:

$$F_{measure} = \frac{2\times Recall\times Precision}{Recall+Precision} = \frac{2TP}{2TP+FP+FN} \quad (3)$$

It should be noted that in the reporting tables the number of rules generated by classification methods is also represented because of the importance of this criterion. The huge number of rules can be a sign of overfitting. On the other hand, when a rule set is generated, the point is the lack of comprehensiveness. So an acceptable trade-off between Accuracy, *F-measure,* and rule numbers should be created.

3.4 Parameter Tuning

To tune the parameters of the previously compared methods, all of them have been implemented 100 times. Since REP is the selected method of pruning, two parameters, the number of folds and the minimum number of instances, should be tuned. Based on the results, the number of folds has been fixed at 3 because changing this parameter would not make any significant changes in the results. Therefore, the number of folds represents the results.

Table 3 shows the results of comparing the various values of the minimum number of instances (Min Num. Ins.) parameter for the 3 rule mining methods. The first result indicates that increasing this parameter decreases the number of rules and the other two performance evaluation criteria: Accuracy and F-measure. The higher the value assigned to these parameters, the more precise the classification method will be, but the excessive number of rules is unacceptable. Reviewing the results shows that Accuracy and F-measure have not been adversely affected by increasing this parameter while the number of rules has been decreasing to make the rule set more apprehensible. Therefore, 500 and 1000 would be the most appropriate values for this parameter to generate a precise and comprehensive rule set representing all features of the data set.

3.5 Evaluation Results

As explained previously, Accuracy and F-measure have been applied to evaluate the compared methods. To compare the results in pairs, as shown in Table 3, a paired T-test is used. Thus, the first step is to test the normality of the results for both parameters (Accuracy and F-measure) using the Kolmogorov–Smirnov test. Table 4 shows the p-value of this test by setting the confidence level at 95%. Considering that the p-value of both parameters for all methods is greater than 0.05, the null hypothesis assumes the data is normal. After proving the normality of the evaluation parameters, a paired T-test has been used to compare the classification rule mining methods in pairs. By setting the confidence level at 95%, and with no significant difference between the averages of the two compared methods, the null hypothesis is rejected when the p-value is less than 0.05.

Table 3. SENSITIVITY ANALYSIS OF the “MINIMUM NUMBER OF INSTANCES” PARAMETER FOR COMPARED METHODS

Classification rule mining method	Num. of folds	Min Num. Ins.	Number of rules	Accuracy (%)	F-Measure
PART	3	2	883	94.4687	0.944
		50	160	92.6758	0.926
		80	135	92.3682	0.923
		100	115	92.0517	0.92
		200	82	91.4269	0.914
		300	54	90.6672	0.906
		500	48	88.8614	0.887
		1000	33	86.3353	0.858
J48	3	2	1569	94.8789	0.948
		50	302	92.6982	0.926
		80	222	92.3269	0.922
		100	185	92.0876	0.92
		200	147	91.6933	0.916
		300	131	90.7934	0.907
		500	94	89.1343	0.89
		1000	72	85.1831	0.844
JRip	3	2	76	92.2340	0.922
		50	59	90.8989	0.907
		80	51	90.791	0.906
		100	40	90.669	0.904
		200	33	90.1	0.914
		300	26	89.6582	0.894
		500	21	88.1146	0.878
		1000	13	84.6703	0.836

Table 5 shows the obtained p-value of this T-test as well as the average value of the two parameters (Accuracy and F-measure) for compared methods. The immediate conclusion of this table is that based on the p-value the two methods, PART and J48, do not differ significantly in terms of average Accuracy and F-measure at the confidence level of 95% (p-value>0.05). On the other hand, considering the average values of Accuracy and F-measure (p-value=0), very different results have been generated for the PART-JRip pair and J48-JRip pair. The average of these evaluation parameters for JRip is less than PART and 48. This means that the two methods PART and J48, yield more precise results than JRip. However, to get insights into the analyzed data set, we must choose a method and find a final rule set. Even though PART has generated rules with almost the same Accuracy and F-measure as J48, its rule numbers are considerably lower (Table 3). In conclusion, of the studied data, balancing different criteria has led to the selection of PART as the classification rule mining method.

Table 4. RESULTS OF KOLMOGOROV–SMIRNOV TEST TO CHECK THE NORMALITY OF RESULTS

Classification rule mining method	**p-value**	
	Accuracy	**F-measure**
PART	0.646	0.508
J48	0.347	0.257
JRip	0.43	0.592

Table 5. RESULTS OF PAIRED T-TEST FOR COMPARED CLASSIFICATION RULE MINING METHODS

Compared methods	Output	Evaluation parameters	
		Accuracy	F-measure
PART-J48	P-value	0.14	0.181
	The average value of PART	0.914	0.9128
	The average value of J48	0.915	0.9139
PART-JRip	P-value	0	0
	The average value of PART	0.914	0.9128
	The average value of JRip	0.895	0.8930
J48-JRip	P-value	0	0
	The average value of J48	0.915	0.9139
	The average value of JRip	0.895	0.8930

CONCLUSIONS

In this paper, by considering the number of bidding blocks of generating units the efficiency of IWEM has been analyzed. The main walks of this analytical approach were identifying factors that could meaningfully affect block numbers and extracting If-Then rules using classification rule mining methods to get insights into generation units' bidding behavior. The results of comparing three different methods by statistical tests show that a partial decision tree (PART) provides relatively more acceptable results than the other methods. Future works could include applying machine-learning algorithms to gain a deeper understanding of electricity markets considering various aspects of them.

REFERENCES

Alvarez-Ramirez, J., & Escarela-Perez, R. (2010). Time-dependent correlations in electricity markets. Energy Economics, 32(2), 269-277.

Alvarez-Ramirez, J., Escarela-Perez, R., Espinosa-Perez, G., & Urrea, R. (2009). Dynamics of electricity market correlations. Physica A: Statistical Mechanics and its Applications, 388(11), 2173-2188.

Asgari, M. H., & Monsef, H. (2010). Market power analysis for the Iranian electricity market. Energy Policy, 38(10), 5582-5599.

Bemš, J., Králík, T., Knapek, J., & Kradeckaia, A. (2016). Bidding zones reconfiguration current issues literature review, criterions and social welfare. Paper presented at the 2016 2nd International Conference on Intelligent Green Building and Smart Grid (IGBSG).

Chernenko, N. (2015). Market power issues in the reformed Russian electricity supply industry. Energy Economics, 50, 315-323.

Chicco, G., Colella, P., Griffone, A., Russo, A., Zhang, Y., Carlini, E. M., Nuzzo, G. (2019). Overview of the Clustering Algorithms for the Formation of the Bidding Zones. Paper presented at the 2019 54th International Universities Power Engineering Conference (UPEC).

Cramton, P. (2004). Competitive bidding behavior in uniform-price auction markets. Paper presented at the 37th Annual Hawaii International Conference on System Sciences, 2004. Proceedings of the.

Emami, I. T., Abyaneh, H. A., Zareipour, H., & Bakhshai, A. (2020). A novel simulation-based method for assessment of collusion potential in wholesale electricity markets. Sustainable Energy, Grids and Networks, 24, 100405.

Esposito, F., Malerba, D., Semeraro, G., & Kay, J. (1997). A comparative analysis of methods for pruning decision trees. IEEE transactions on pattern analysis and machine intelligence, 19(5), 476-491.

Ferreira, J., Ramos, S., Vale, Z., & Soares, J. (2011). A data-mining-based methodology for transmission expansion planning. IEEE intelligent systems(2), 28-37.

Frank, E., & Witten, I. H. (1998). Generating accurate rule sets without global optimization.

Han, J., Kamber, M., & Mining, D. (2006). Concepts and techniques. Morgan Kaufmann, 340, 94104-93205.

Huang, D., Zareipour, H., Rosehart, W. D., & Amjady, N. (2012). Data mining for electricity price classification and the application to demand-side management. IEEE Transactions on Smart Grid, 3(2), 808-817.

Kohavi, R., & John, G. H. (1997). Wrappers for feature subset selection. Artificial intelligence, 97(1-2), 273-324.

Narain, A., Srivastava, S., & Singh, S. (2020). Congestion management approaches in restructured power system: Key issues and challenges. The Electricity Journal, 33(3), 106715.

Nazemi, A., & Mashayekhi, M. (2015). Competitiveness assessment of Iran's restructured electricity market. Energy Economics, 49, 308-316.

Peco, J., Sánchez-Úbeda, E., & Gómez, T. (1999). Enhancing optimal transmission or subtransmission planning by using decision trees. Paper presented at the PowerTech Budapest 99. Abstract Records.(Cat. No. 99EX376).

Quinlan, J. R. (1986). Induction of decision trees. Machine learning, 1(1), 81-106.

Quinlan, J. R. (1987). Simplifying decision trees. International journal of man-machine studies, 27(3), 221-234.

Quinlan, J. R. (2014). C4. 5: programs for machine learning: Elsevier.

Rostamnia, N., & Rashid, T. A. (2019). Investigating the effect of competitiveness power in estimating the average weighted price in electricity market. The Electricity Journal, 32(8), 106628.

Saez, Y., Mochon, A., Corona, L., & Isasi, P. (2019). Integration in the European electricity market: A machine learning-based convergence analysis for the Central Western Europe region. Energy Policy, 132, 549-566.

Sánchez-Úbeda, E., Peco, J., Raymont, P., Gomez, T., Bañales, S., & Hernández, A. (2001). Application of data mining techniques to identify structural congestion problems under uncertainty. Paper presented at the 2001 IEEE Porto Power Tech Proceedings (Cat. No. 01EX502).

Shao, Z., Zheng, Q., Yang, S., Gao, F., Cheng, M., Zhang, Q., & Liu, C. (2020). Modeling and forecasting the electricity clearing price: A novel BELM based pattern classification framework and a comparative analytic study on multi-layer BELM and LSTM. Energy Economics, 104648.

Spees, K., & Lave, L. B. (2007). Demand response and electricity market efficiency. The Electricity Journal, 20(3), 69-85.

Staudt, P., Rausch, B., Gärttner, J., & Weinhardt, C. (2019). Predicting Transmission Line Congestion in Energy Systems with a High Share of Renewables. Paper presented at the 2019 IEEE Milan PowerTech.

Taheri, I., Rashidi Nejad, M., Badri, A., & Abdollahi, A. (2013). The study of GENCOs' bidding strategies in a pool-based electricity market using cooperative and non-cooperative game theory. Journal Of Electrical Systems And Signals, 1(1).

Taheri, I., Samani, E., Abyaneh, H. A., Mohsenian-Rad, H., & Bakhshai, A. (2022). A Conceptual Analysis of Equilibrium Bidding Strategy in a Combined Oligopoly and Oligopsony Wholesale Electricity Market. IEEE Transactions on Power Systems.

Van den Bergh, K., Boury, J., & Delarue, E. (2016). The flow-based market coupling in central western europe: Concepts and definitions. The Electricity Journal, 29(1), 24-29.

Yousefi, G. R., Kaviri, S. M., Latify, M. A., & Rahmati, I. (2017). Electricity industry restructuring in Iran. Energy Policy, 108, 212-226.

Zamani-Dehkordi, P., Rakai, L., & Zareipour, H. (2015). A Data-Driven Method to Detect the Abnormal Instances in an Electricity Market. Paper presented at the 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA).

Zareipour, H., Janjani, A., Leung, H., Motamedi, A., & Schellenberg, A. (2010). Classification of future electricity market prices. IEEE Transactions on Power Systems, 26(1), 165-173.