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Research Article

Predicting the Creation of Smart Grids considering the Role of Big Data in North America's Electricity Market

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Abstract

Using dual-bandwidth digital technology, the smart grid delivers energy from manufacturers to customers, saving consumers energy by controlling their home appliances, reducing costs and enhancing reliability and transparency. The smart grid on the one hand and the shaping of the electricity market, on the other hand, have created a huge amount of data every day through the daily interactions of electricity and to decide which market players to include manufacturers, transmitters, distributors and in the near future on smart grids for electricity consumers, storage and then be analyzed. This huge amount of data, despite the many benefits it can bring, can cause problems in data storage, display and analysis. For example, one of the most important tasks of North America's electricity market management is to forecast electricity prices for future periods based on stored historical data and because of the type of data produced in this area of the big data typ. Data has problems with different fields, especially in data analysis. In this paper, the role of modern data mining methods for big data analysis is compared by comparing two traditional and new data mining methods and performing statistical experiments. The results of this paper show that a slight improvement in electricity price forecasts due to high volume of electricity exchanges can bring incredible savings to the players in this field. Therefore, the use of modern data mining methods in this field is very important and practical.

Keywords: *electricity market, smart grid, big data, data mining*

1. Introduction

Electricity prices will be set around the world in the near future in the electricity market. The electricity market is a system of supply and demand for electricity that is set up to determine the price of electricity [1]. In the new structure of the power industry, the systems mentioned above operate independently, as opposed to the old structure of production, distribution and transmission management [2]. In the meantime, the electricity market will act as an intermediary between these systems and divide the economic structure of the electricity industry into four wholesalers, transit, wholesalers and retailers [3]. In this structure, the goal of buying and selling electricity in a competitive market between buyers who are consumers of electricity and sellers who are power plants is mentioned. In this structure, based on the data, such as the expressed production capability, the transmissible production capability, the average variable cost of power plant production, etc., which is exchanged between buyers and sellers, the actors in this field make their decisions [4].

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The accuracy and accuracy of the data in this domain will have a unique impact on the accurate estimation of its parameters [5]. There are many sources of data generation in the electricity market, and with the addition of power plants, distribution, transmission and regional electricity companies and all customers part of the system, we will see a growing number of data sources in the coming years [6]. The number of parameters for which data is being collected in the industry is also growing [7]. So the growth of data in this industry is driven by the growth of resources and parameters. On the other hand, the electricity industry is confronted with an emerging phenomenon called smart grids, in which the future of the electricity industry depends on the smart grid [8]. The smart grid will sooner or later be deployed around the world. This network transmits energy from manufacturers to customers using two-way digital technology, saving consumers energy by controlling their home appliances, reducing costs and increasing reliability and transparency [9]. Such a modern electric grid is being pursued by many governments as a way of managing energy independence, global warming, and emerging issues [10]. The smart grid can be defined in two ways. Many articles and books refer to the smart grid as the image and outlook that a future grid should have. From a regulatory perspective, the definition of a smart grid is more commonly used where the definition of challenges is specifically mentioned [11]. For example, in the definition provided by the European energy regulatory authority, smart grid is a network that connects all users (both generator and consumer) in a cost-effective and efficient way and in order to increase economic efficiency, system stability Integrated power with low losses and high quality and safe [12]. The smart grid is therefore a two-way communication platform in which information plays a key role in the distribution of energy. One of the most important features of the electricity market is the maximum participation in the electricity market [13]. Active involvement of consumers and subscribers along with distribution companies in the electricity markets has many benefits for the transmission grid and the electricity distribution and production companies [14]. The smart grid provides consumers with information on the amount and cost of electricity consumed and it is possible for consumers to operate in new electricity markets. The flow of accurate information between power companies and consumers enables them to vary the amount of energy consumed based on the balance between demand power and local generation resources and existing electricity grid [15]. Undoubtedly, the volume of data exchanged in the electricity market will create dramatic changes in the near future with the creation of the necessary infrastructure for the global implementation of the smart grid [16]. This paper studies the future of the electricity market by implementing a smart grid and explores the enormous data of this area and its challenges and opportunities by studying the case study of North America's electricity market and describing the current situation.

2. Current electricity market structure and data volume

The electricity industry was governed by most countries until the last two decades of the 19th century with an integrated structure that was responsible for the production, distribution, transmission and service of customers. "This is the first time in the year that the question of why power companies need to be structured?" The monopoly nature of the electricity industry was challenged and the idea of generating public competition in production was taken into consideration [17].

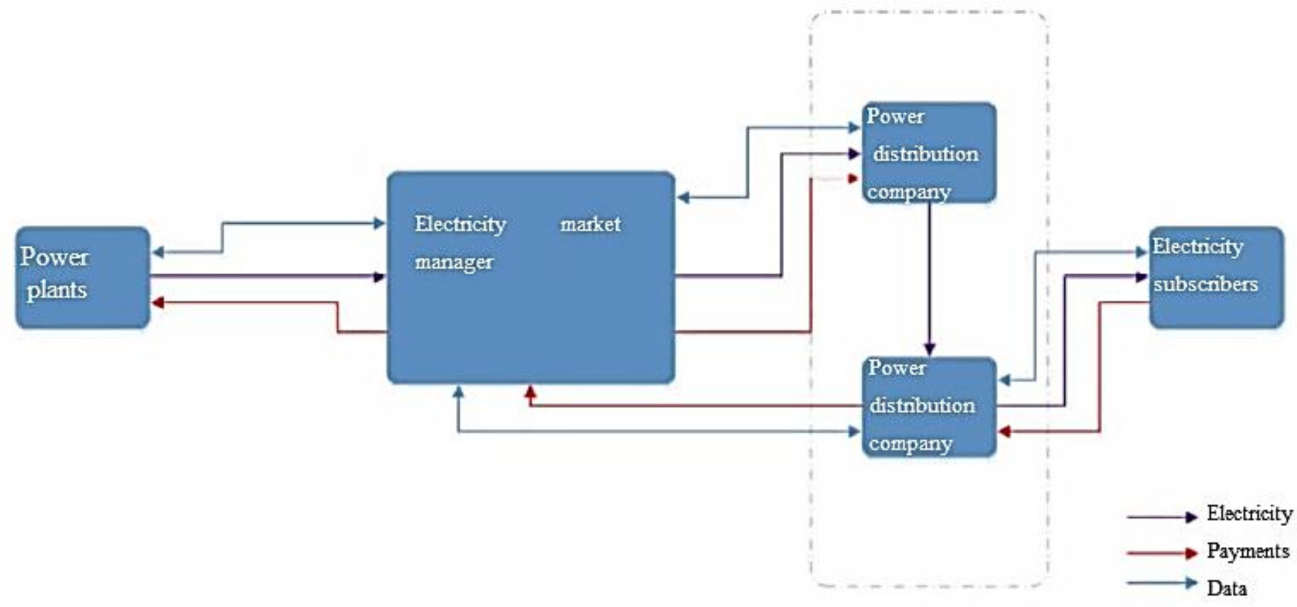

Figure 1: The current structure of the electricity market

North America, including Canada and Mexico, are among the first countries to privatize and compete in the electricity industry in the year. Following the successful North American experience, with the passage of the British Electricity Act of 1989, the country's electricity industry became the first European country to undergo major structural changes [18].

The restructuring and regulatory changes in the US electricity industry have a later date than the UK. After the US, structural changes were first followed in Argentina and Chile, followed by European and Asian countries. The idea of using private investment in the electricity industry, which in the 1970s changed the public business environment in the country in the early years of the construction period and then the borrowing process from the public sector and its banking system, has gradually taken a serious and practical form. He took it upon himself [19].

This trend has slowed somewhat in the years since 1998 because of public resistance to the government's economic situation, and in particular economic adjustment policies, and, more importantly, to pressures on the low-income and low-income communities. It came out right and logically [20].

In the year 2000, as the US countries needed to attract private sector capital and develop and expand the electricity industry, studies of the restructuring of the electricity industry began again, summarizing past experiences and making executive decisions. 2001 was the year of finalizing executive decisions.

Finally, this year a conceptual outline of the electricity industry restructuring was adopted, and in the new structure of the electricity industry unlike the previous structure where the distribution and transmission sectors were unified management, the new structure of each of these units operated independently and has separate management. The exchanges in this structure are based on Figure 1.

In this structure, for the purpose of pricing and buying electricity, data needs to be exchanged between different sectors of the industry with the management of the electricity market. In the current structure of the electricity market, power plants are the sellers and buyers of electricity distribution companies.

This data should be stored quickly and without interruption in day-to-day management of the electricity market and then shared between buyers and sellers. In this structure, it is necessary to determine the fair price the day before and after the equilibrium price has been obtained, after the required load of the buyers or the distribution companies is announced and the price quoted by the vendors of the power industry or the same power plants. All data exchanged in the electricity industry is for the purpose of identifying and estimating a reasonable price for the electricity industry that has the smallest difference with the actual value. Therefore, in the new structure, the map of production and exchange of data is greater and has a major impact on the electricity market [21].

2-1 The future structure of the electricity market

A smart grid (digital grid) technology transmits energy from manufacturers to customers, using digital bi-directional technology to reduce energy consumption, reduce costs and improve reliability and transparency by controlling consumers' home appliances. Such a modern electric grid is being pursued by many governments as a way of managing energy independence, global warming, and emerging issues [22].

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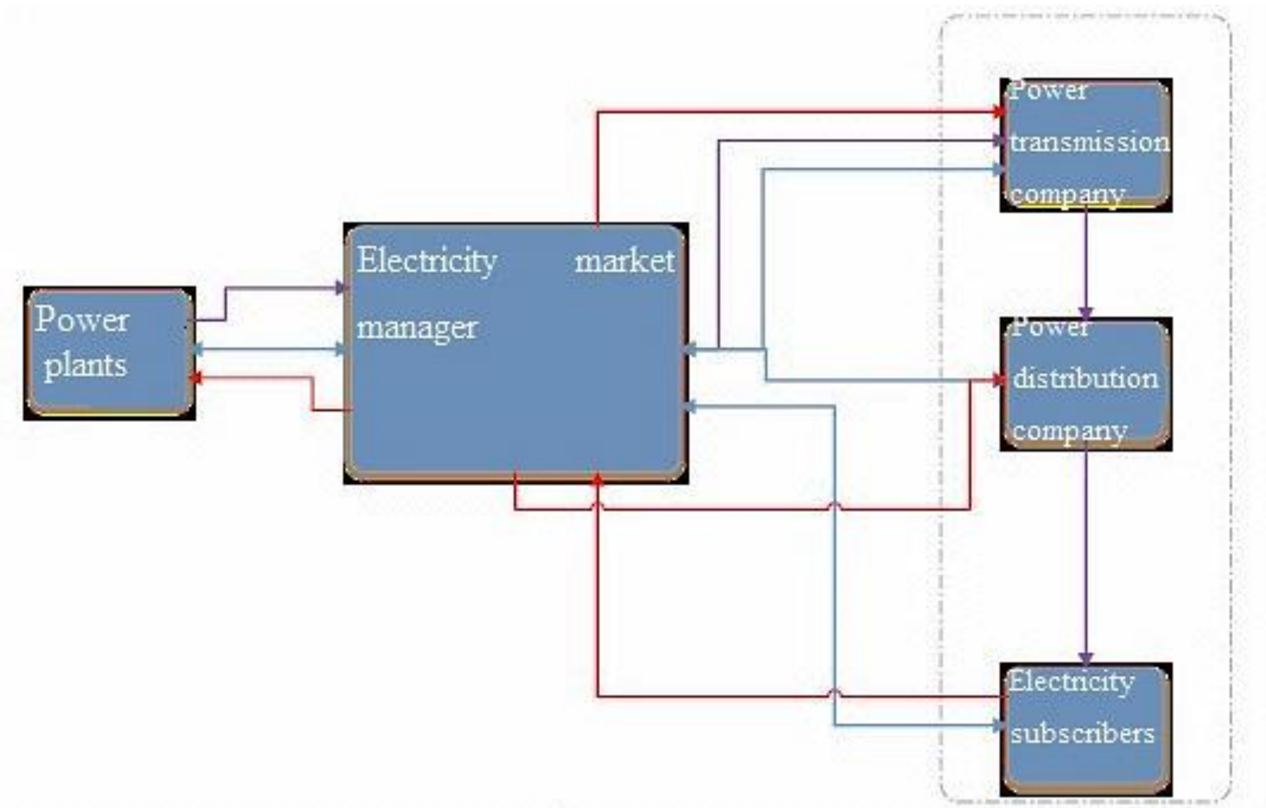

Figure 2: Future structure of the electricity market

For example, in the definition provided by the European energy regulatory authority, a smart grid is a network that connects all users (both generator and consumer) in a cost-effective and efficient way, and in order to increase economic efficiency, sustain the power system with low losses and high quality and safely integrated [23].

Now, if we look at the future of the electricity industry, which is smart, in the presence of the electricity market, we will see that electricity subscribers, from the largest to industrial units, to the smallest to ordinary household subscribers, can directly and indirectly present in the electricity market and receive or send data from electricity market management and based on data such as the rate of electricity generation of each power plant and the rate of transmission by electricity transmission companies or the rate of electricity distribution by electricity distribution companies, instantaneous and under network infrastructure is the optimal choice for electricity consumption. This smart structure, although not currently available with the current capabilities, will be implemented in the near future in our world and in our country [24].

It is impossible to imagine the volume of data being exchanged in a situation where there are numerous consumers and a large number of generators, and the electricity management company must think of a way to store and analyze them (Figure 2).

2-2 New smart power market structure, new challenges and solutions

Overall, the future of North America's smart power market is a very different one from the current structure of the power market and requires solutions to address the enormous volume of data generated. As stated, the primary purpose of the electricity market is to correctly predict the rate of consumption of electricity. The rate is calculated for each power plant and is purchased by electricity subscribers based on other parameters, including transmission and distribution rates. Data mining is one of the attractive ways to predict electricity rates for the coming period as past data provide useful information to the electricity market manager. But as stated, given the enormous volume of data generation in the future of smart grid is inevitable, traditional data mining methods will not solve this problem, for example, one of the most popular k-means data mining methods. This method has time complexity kd with k record number and d number of parameters both of which are incredibly growing in the near future in smart grid. So analyzing this volume of data is actually one of the difficult issues. Therefore, if the data in this electricity market need to be analyzed in an instant, it is necessary to use new methods to ensure the quality of the produced answers in addition to time. The new methods presented in data mining are the solution to this problem. In the field of big data analysis, various methods, software and methods have been proposed. One of the recently introduced and exciting research areas facing industrial engineering is machine learning in data mining. The structure of the smart electricity market seems to be in dire need of these approaches in the future as data analysis in the coming years has made it impossible for the electricity management company without these new algorithms and methods.

The purpose of the electricity market is to determine the fair price of electricity for the futures market. As has been shown in the previous sections, the volume of data produced in the electricity market is very high, so that data mining will be severely constrained by traditional data mining methods. For this purpose, it seems necessary to conduct meta-data mining in order to predict the speed and quality of the solutions or the fair price of electricity. Following is a traditional data mining method and a new meta-data mining method to explore this issue.

2-3 Advantages of data analysis with modern algorithms of big data

In this section, two statistical tests will be defined. The first experiment will determine the effect of data mining method and the other volume of data mining data on the accuracy of price prediction which will be considered as response variable. In the second experiment, the rate of improvement in the price forecasts is tested by past data.

2-4 K^2 experiment to investigate the impact of data volume and data mining methods

This part of the factorial experiment is used to investigate the effect of the variables "data mining volume" and "data mining method" on the response variable "price prediction accuracy". Factorizing the volume of data produced means examining the impact of data interference in previous years on the accuracy of price forecasts, meaning whether the data of a year are compared to the total data collected from 1 last year, whether have an impact on accuracy. The data mining method will also be examined in this method. In this paper, two methods of SVM or parallel vector machines, that is the traditional data mining method, with the SVMIGA metadata method, which combines the method of parallel vector machines and the genetic algorithm proposed by Lee J et al (2014) and its effect on the accuracy of forecasts is tested.

3. Results

The assumptions and results of the experimental treatment combinations are as follows:

Table (1) Assumptions and results of 2^k experimental treatment combinations

Factors		Treatment	Repetition						
The volume of data mined data	Data mining method		1	2	3	4	5	6	Total
-	-	2015 and SVM only	79.6	82.3	83.2	85.3	90.3	90.9	87.9
+	-	From 2002 to 2015 and SVM	Failure to run the test due to the inability of the algorithm to cluster huge volumes of data						-
-	+	Only 2015 and SVMIGA	91.2	92.6	93.5	94.8	92.3	89.3	92.7
+	+	From 2002 to 2015 and SVMIGA	94.7	95.3	96.3	97.4	97.1	98.3	96.7

Table (2) Clustering results by SVMIGA algorithm

Cluster parameter	1	2	3	....	38	Electricity price forecast	The actual amount of electricity price
1	3600000	505000	5700000	....	13.2	312000	.
2	3540000	6600000	7840000	....	15.4	314800	.
.	.	.	.	.	.	.	.
8	2350000	5200000	7800000		8.9	554000	546670
.	.	.	.	....	.	.	.
100	3050000	5100000	7000000	....	11.2	475600	.

```
Analysis of Variance

Source     DF   Adj SS    Adj MS   F-Value  P-Value
Model       2   439.71   219.857     24.70    0.000
  Linear    2   439.71   219.857     24.70    0.000
    A       1    57.64    57.641      6.47    0.022
    B       1   172.45   172.445     19.37    0.001
Error      15   133.53     8.902
Total      17   573.25
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Figure (3) Results of two-factor design analysis of variance

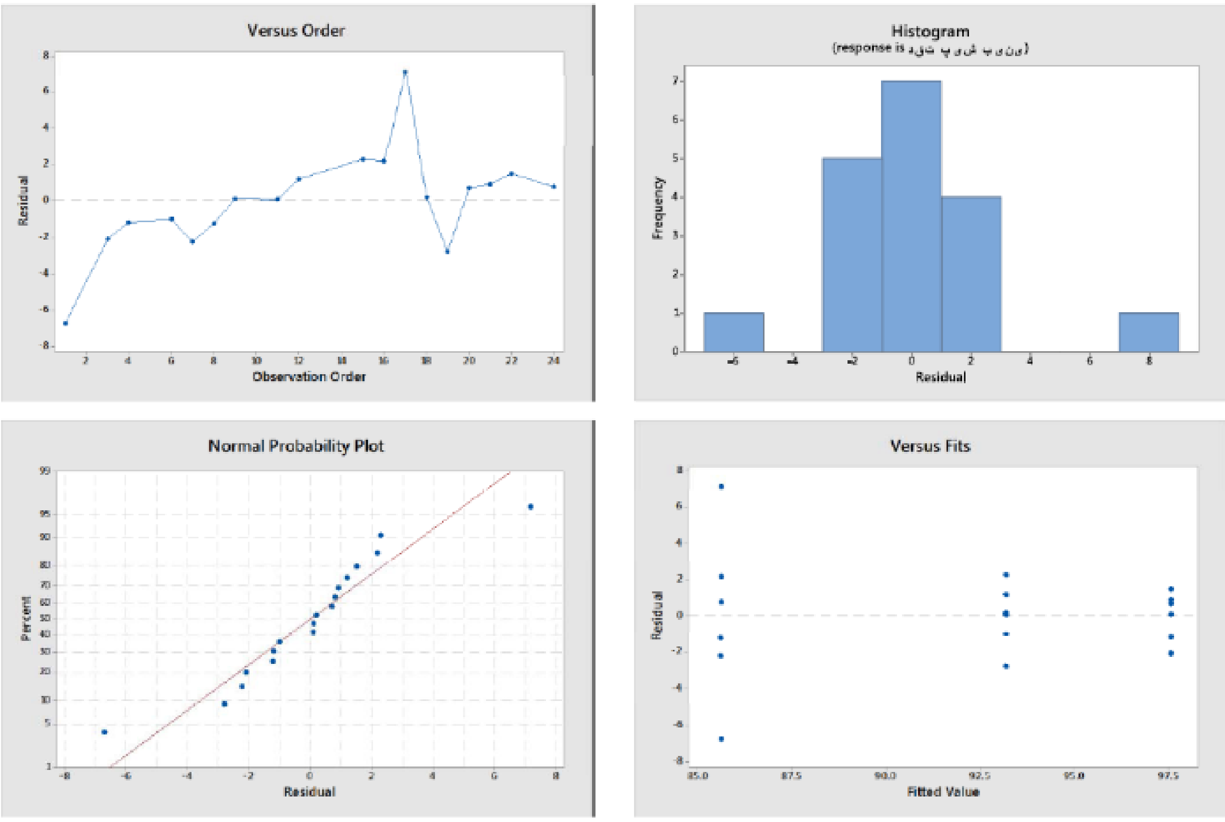

Figure (4) The remaining diagrams of the two-factor design

Table 2 shows cluster centers resulting from data clustering between 2002 and 2015, using the S MIGA algorithm, for example, in the second iteration. As shown in the table, the closest cluster center to the data of the forecast period is cluster 8, which can be measured by the accuracy of the actual value of the price approved for this period:

The results of the two-factor design experiment by 17 Minitab software with two levels show the effectiveness of "data mined data volume" and "data mining method" and also the interaction of these two factors with the 95% confidence coefficient will be significant.

3.1 Test the difference between the means to evaluate the improvement in the results of data mining with new methods

In this experiment, the assumption of equality of averages in the two running modes of the SVMIGA algorithm for total data analysis (μ_x) in the database of the Iranian electricity market with the average error is predicted for the case where data analysis is sufficient with only one year data. The past and its data mining have been analyzed by the traditional method of (SVM)μ_y, compared. The assumptions required to run the test and its results are as described in Table 3.

Table (3) Assumptions of the mean difference test

Assumptions	Test statistics	Reception area for Z0
$H_0: \mu_x - \mu_y = \delta$ $H_1: \mu_x - \mu_y \geq \delta$	$t_0 = \frac{(\overline{X} - \overline{Y} - \delta)}{\sqrt{\left(S_x^2/n_x\right) + \left(S_y^2/n_y\right)}}$	$(-\infty . t_\alpha]$

In this test, the value of δ as an adjustable parameter is changed by trial and error method, and the high values are reduced to low values to make the H1 assumption significant. The data mined samples in the previous step will also be used for this test. The results of the implementation of the mean difference test with the assumption that the variance in the society is not clear and the 95% confidence interval in the Minitab software version 17 are as follows:

```
Two-sample T for X vs Y

N   Mean   StDev   SE Mean
X  6  97.58   1.37     0.56
Y  6  86.42   5.20      2.1
Difference = μ (X) - μ (Y)
Estimate for difference:  11.17
95% CI for difference:  (5.52, 16.81)
                T-Test of difference = 6 (vs ≠): T-Value = 2.35  P-Value = 0.065  DF = 5
```

Figure (5) Variation analysis results of mean difference

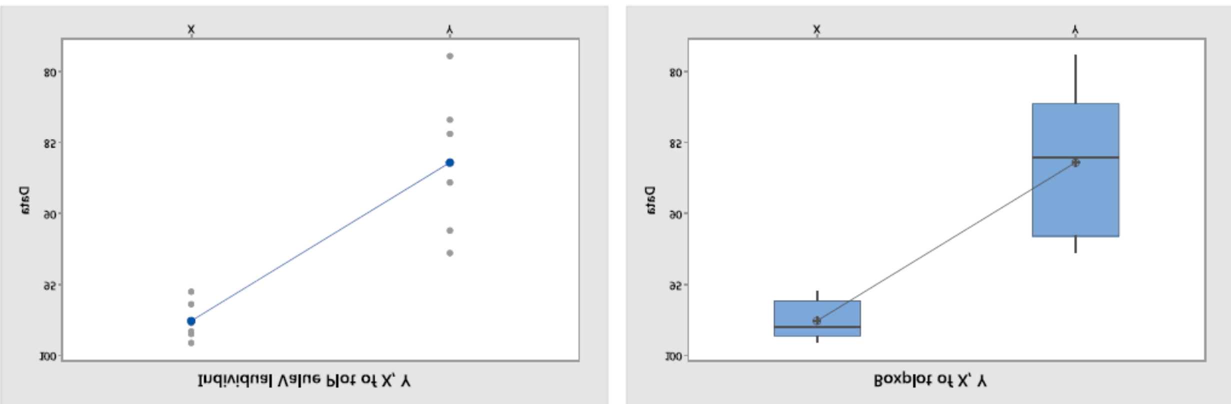

Figure (6) Boxplot and individual value charts

As can be seen from the test results in figure 5, the 6% difference is significant and the assumption of one will be accepted. As stated this difference is between the implementation of the meta-heuristic algorithm on big data and the implementation of the traditional algorithm on limited data.

Conclusion

As mentioned in the previous sections, the data of the electricity market, due to the changes that can be seen in its structural process, is leading to the creation of a huge amount of data that every day from countless consumers, a large number of transmission companies, distributors. Numerous power plants are being built and will be handed over to the electricity market management for the required analysis, the most important of which is the forecast of electricity prices for the next period. Moreover, traditional data mining methods are not a good way to analyze this huge amount of data that is being stored in the smart electricity market, and therefore methods should be used that are suitable for analyzing this type of data. . Based on previous experiments and data mining with SVM and SVMIGA methods, the results show a significant effect of two factors: "volume of data mined data" and "data mining method" on "electricity price forecasting accuracy". It also has a 6% improvement in electricity price forecasting based on historical data available in the database. If this amount of improvement is considered, the following calculations are assumed:

E (Average cost savings for all electricity market agents per hour in 2015) = E (average electricity price per hour in 2015) * E (average volume of electricity exchanges per hour in 2015) * Percentage improvement in forecasting

324000RLS * (31025MG/l) * 0.05 = 628258800RLS

These calculations show that the improvement in electricity price forecasting, due to the high volume of exchanges in this market, can provide incredible savings in total and on average for buyers and sellers in this field. Savings can pave the way for better investments for actors in this field. Therefore, it seems that the use of new solutions in the electricity market and the development of existing algorithms in this field, whose vacancy is felt in this market, seem to pave the way for the unnecessary cost to producers and save the cost of consumers. However, in addition to accurate forecasting of electricity prices, which is one of the tasks of this unit, the analysis of data by the electricity market manager will pave the way for production management, transmission, distribution and consumption and more accurate planning.

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