An Application of the Novel Hybrid Model in Monthly Prediction of the Electricity Cost in the Iraqi Market System

Ayad Abas Hasan[1], Ali Ihsan Alanssari[2], Ahmed Majed Althahabi[3], Ali H. A.[4], Kadhum Al-Majdi[5], Zainab.R.Abdulsada[6]

[1]*College of media/ The Islamic university in Najaf, iraq*
[2]*Department of Medical Laboratories Technology, Al-Nisour University College, Nisour Seq. Karkh, Baghdad, Iraq*
[3]*Al-Manara College For Medical Sciences, Maysan, Iraq*
[4]*Department of Medical Laboratory Technics, Al-Zahrawi University College, Karbala, Iraq*
[5]*Department of biomedical engineering/ Ashur University College/Baghdad/ Iraq*
[6]*College of Technical Engineering, National University of Science and Technology, Dhi Qar, 64001, Iraq*

Electricity-related industries have changed organizationally. Its monopolistic structure is competitive-like. This market's transactions are based on buyers and sellers' one- or more-day-old proposals to buy and sell electricity. The purpose of this study was to examine the methods proposed to enhance the performance of the support vector machine model and their application to the process of predicting future electricity prices. A single attempt was made to estimate the model's performance using a wavelet combination. In the electricity markets of Spain and Iraq, which are real systems with readily accessible data, the proposed method was discussed and investigated. The most significant aspect of this study is the application of and the support vector machine training model to determine the optimal inputs while accounting for uncertainty. The results showed that the price prediction ability of the proposed model is good in both Spanish and Iraqi system. MAPE, MAE, and RMSE values for the test phase are 2.22, 3.12, and 4.01, while those for Iraqi market system and the training phase are 2.76, 3.71, and 4.32.

Keywords: Wavelet; Electericity Market System; Support Vector Machine.

1. Introduction

In recent years, there has been a shift in the organizational structure of industries that deal with electricity [1]. Its monopolistic structure is more similar to that of a competitive one [2]. In this market, buyers and sellers submit proposals for the purchase and sale of electricity to the market one or more days in advance, and the transactions in the electricity market are based on these proposals [3]. Under these conditions, electricity price forecasting is not only essential for pricing but also plays an essential role in assisting operators of power plants in determining the most effective method of resource utilization [4], [5]. A review of the studies reveals that the presence of some unique characteristics in the electricity market, innovation, and dramatic changes in the market have contributed to a significant increase in the amount of prediction error [6]–[8].

The results of the comparison between the forecast made by ARIMA models and their combination with wavelet show that the combination of ARIMA models and wavelet models will improve forecast results while simultaneously reducing the amount of error in the forecast [9]. The market reveals that the majority of production units use only one or two power blocks for pricing in the market, and approximately 15% of them, in a strategic move, identify part of their power blocks in the market. This information is pertinent to the investigation of the relationship between the pricing pattern of production units and their effect on price. In addition, a comparison of the total distribution of power blocks in terms of price at various hours reveals that the pricing behavior of approximately one-third of the production units contributing to the base load is either uneconomical or excessively cautious [10]. According to the findings of a study on electricity market prices that was carried out using the time series methodology and focused on the ARMAX-GARCH models, it was discovered that these models have a high level of effectiveness in the field of risk management [11]. Furthermore, the investigation of various kinds of ARMAX-GARCH models based on their statistical properties and capacity to evaluate and estimate the time series of electricity market prices demonstrates that these models are able to predict price changes. This demonstrates that under the circumstances that currently exist in Iran's electricity market, information asymmetry plays a lesser role, and standard GARCH models are the best simulations currently available [12]. Catalão et al. [13] have used the technique of fast learning machine (ELM) and also have made use of wavelet transformation in addition to a combination of neural network (ANN) and fuzzy logic in order to provide a short-term forecast model of electricity prices in a market that is competitive. This was done to provide a model that could predict the prices of electricity in the near future. The combination of the proposed method with the wavelet technique in forecasting the price of electricity markets in Ontario, New York, and Italy demonstrates that the proposed method is among the most appropriate techniques for price forecasting [14]. The research that was conducted to predict the daily cost of electricity with an enhanced neural network that was based on it demonstrates the high capability of this algorithm in better prediction compared to other methods using the wavelet transform and the chaotic method of gravitational search. Both methods are based on the wavelet transform. Additionally, the results demonstrated that the electoral algorithm is quite effective in sorting the data that were divided using wavelet transform [15].

The goal of this study was to investigate the methods that have been presented to improve the performance of the support vector machine model and their application in the process of predicting future electricity prices. A single attempt to estimate the performance of the model was made using a wavelet combination. The proposed method was discussed and investigated in the electricity markets of Spain and Iraq, which are real systems with readily available information. The use of an SVM training model to determine the best inputs considering the uncertainty is the aspect of this study that stands out as the most significant.

2. Materials And Mehods

A combined wavelet transform method and SVM is used in this study with the motivation of maximum performance prediction and the elimination of the shortcomings of the previous methods. This method is used to reduce fluctuations in the input noise data and increase the prediction accuracy based on a non-noise structure for training.

2.1 Support Vector System

SVM is one of the methods for supervised learning. SVM is a classifier within a branch of Kernel Methods [16]. This was a successful application of machine learning. It is employed for the classification, estimation, and estimation of the data fitting function. Therefore, the classification of the data or fitting function is as error-free as possible [17]. This is a relatively new method that has performed well in recent years compared to the method that has been in use for several decades. Perceptron neural networks comprise the older classification systems. Linear classification of data is the foundation of SVM classifier. In the linear classification of the data, the line with the most reliable margin was selected. QP methods, which are well-known methods for solving constrained problems, are used to solve the equation to determine the optimal line for the data. Prior to linear division, a machine can process data with a high degree of complexity. The phi function leads to a space with significantly greater dimensions (high). Lagrange Duality Theorems are utilized to solve problems with high dimensions. Therefore, instead of the complex phi function with high dimensions, a simpler function, referred to as the multiplication of the phi function, is utilized. Based on statistical learning theory, a SVM was developed by the Cortes and Vapnik [18]. The objective of a SVM is to identify the function (f) x for the learning patterns of the random algorithm x that has training values of y. In other words, the SVM is a model that fits a curve of a certain thickness to the data so that experimental data errors are minimized [19].

As an inner multiplication in high-dimensional space. This significantly reduced the number of calculations required. The polynomial kernel and linear kernel, sigmoidal, and Gaussian RBF are among the different kernel function types.

The Gaussian kernel has a single parameter, g. First, the default value of k (1/k number of features) is applied to this parameter [20]. Subsequently, the values of 1/k and 1 were evaluated. Regarding the convergence of the sigmoid kernel to the answer, we simply assumed a constant value and used the order $1/\ k^2$. It is noteworthy that the sigmoid kernel has no parameters. The linear kernel also lacks these parameters. Therefore, only one execution mode existed. The kernel of the polynomial has two parameters. where d is the polynomial degree of z, which is the first parameter. Numbers 1, 2, 3, and 4 provide solutions to these problems. In addition, -1, 0, and +1 are used for the second parameter, which is a fixed number identified by r, and is a fixed number. The dual optimization problem in a state that is nonseparable and nonlinear is as follows:

$$\begin{cases} \text{Minimize}_{\alpha} - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i\alpha_j y_i y_j k(x_i, x_j) \\ \qquad + \sum_{i=1}^{N} \alpha_i \\ \text{Subject to } 0 \le \alpha_i \le C \\ \sum_{i=1}^{N} \alpha_i y_j = 0 \end{cases} \quad (1)$$

The support vectors are patterns whose corresponding Lagrange coefficients are true in the Eq. 1, $0 \le \alpha_i \le C$ and their number is N_b to calculate b, Eq. 2 is used:

$$\begin{gathered} b_j = y_j - \sum_{i=1}^{N_{SV}} \alpha_i y_i k(SV_i, SV_j) \\ b = \frac{1}{N_b}\sum_{j=1}^{N_b} b_j \end{gathered} \quad (2)$$

The decision function corresponds to Eq. 3:

$$f(x) = \text{Sign}\left(\sum_{i=1}^{N_{SV}} \alpha_i y_i k(x, SV_j) + b\right) \quad (3)$$

2.2 Wavelet transform

The wavelet transform of the wavelet function has two important features: fluctuating and short-lived. $\Psi(x)$ is a wavelet function if and only if its immediate transformation $\Psi(\omega)$ satisfies the condition in Eq. 6 [21].

$$C_g = \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega < \infty \quad (4)$$

This condition is known as the wavelet-acceptance condition (x). This relationship is equivalent to the following equation: In other words, Eq. 7 must be true for the wavelet to satisfy the aforementioned condition [22]:

$$\int_{-\infty}^{+\infty} \Psi(x) dx = 0 \quad (5)$$

Based on this property of functions with zero mean, numerous functions are referred to as wavelet functions. (x) is the mother wavelet function, and the functions used in the analysis were altered in size and location along the studied signal using two mathematical operations: translation and scale. The wavelet coefficients at each point of the signal (value b) and for each value of the scale can be calculated using Eq. 8 and 9 respectively [23], [24].

$$\Psi_{a,b}(x) = \frac{1}{\sqrt{a}}\Psi\left(\frac{x-b}{a}\right); \quad (6)$$

$$f(x)\Psi\left(\frac{x-b}{a}\right)dx = \int_{-\infty}^{+\infty} f(x)\Psi_{a,b}(x)dx. \quad (7)$$

The Eq. 8 can be used to convert scale to frequency.

$$F_a = \frac{F_C}{a.\Delta}, \quad (8)$$

where F_a is the frequency corresponding to the scale of a, $F_C$is the fundamental frequency of the wavelet function (also known as the wavelet's center frequency), and is the sampling period. k represents the moment of a wavelet, and $\Psi(x)$ equals [25], [26]:

$$\int_{-\infty}^{+\infty} x^K\Psi(x)dx = 0. \quad (9)$$

If the following relationship holds, then a wave possesses m Vanishing Moments.

$$\int_{-\infty}^{+\infty} x^K\Psi(x)dx = 0k = 0,1,2,\dots,m-1. \quad (10)$$

Every wavelet function possesses at least one vanishing moment, as demonstrated by the Eq. 11. The Discrete Wavelet Transform (DWT) is also utilized in signal analysis. Transfer and scale parameters are selected discretely in DWT [23].

$$a = 2^{-j}, b = 2^{-jk}, \quad (11)$$

where j and k are real numbers. As a result, by replacing a and b, the Eq. 12 is obtained.

$$\Psi_{j,k}(x) = 2^{\frac{j}{2}}\Psi\left(2^j x - k\right), \quad (12)$$

Taking into account the characteristic relation of a wave function, it can be determined that there are numerous functions with these characteristics. Numerous wavelet functions with various capabilities have been developed in recent years. After choosing the mother wavelet function, wavelet coefficients can be calculated for any value (integer numbers and positive decimals of scale a). Calculating wavelet coefficients for specific values of a is sufficient for a variety of applications.

2.3 Model evaluation criteria

To compare the efficacy of model performance, criteria such as Mean Absolute Value of Percentage Error (MAPE), Mean Absolute Value of Percentage Error (MAE) and the Root Mean Square Error (RMSE) have been utilized. These metrics are related to the following, where X_i and Y_i indicate actual and predicted parameter, respectively [27].

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - Y_i| \quad (13)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_i - Y_i|}{X_i} \quad (14)$$

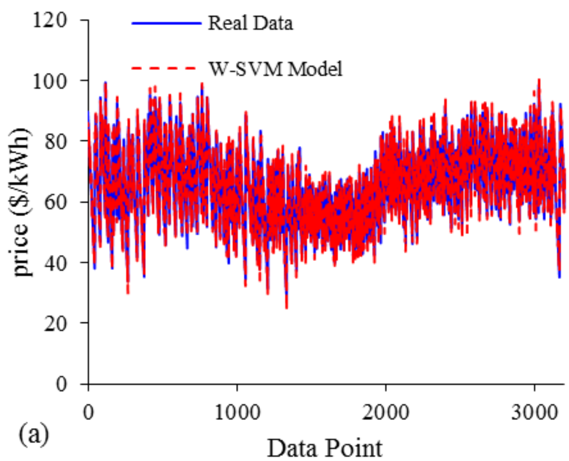
$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \qquad (15)$$

3. Results And Discussion

Spain's real market system was utilized to simulate and predict the price using the proposed algorithm. The selection of this system is based on the veracity and accessibility of information. To predict the price of the Spanish and Iraqi electricity market 100 days in advance, information from the previous 100 days was collected. The observer matrix used to train the data had 1200 members. This entry is a subgroup for P_{t-1}, P_{t-18}, P_{t-24}, P_{t-25}, P_{t-48}, P_{t-96}, and P_t to predict the P_{t+1}. The objective matrix was arranged according to the threshold time and input data to prepare the data for prediction. We used normalization to reduce the differences between the data so that we could use them for training and prediction with fewer fluctuations. In the following the results of application of the hybrid model on the electricity price estimation are evaluate in Spanish and Iraqi system.

3.1 Spanish System case study

Fig. 1 presents the contrast between the actual market price and predicted value generated by the proposed model. The proposed model has been trained using 80% of the available data. Fig. 1-a and 1-b depict the training and testing results of the model in comparison with the actual results. A scatter plot of the results of the actual and model data from x = y line is shown in Fig. 1-c. The price prediction ability of the proposed model is good in this system, as indicated by the evaluation indicators in Table 1. Therefore, the values of evaluation indices MAPE, MAE, and RMSE for the test phase are equal to 2.22, 3.12, and 4.01 whereas the values of MAPE, MAE, and RMSE in this system, and in the training phase are equal to 2.76, 3.71, and 4.32.



(a)

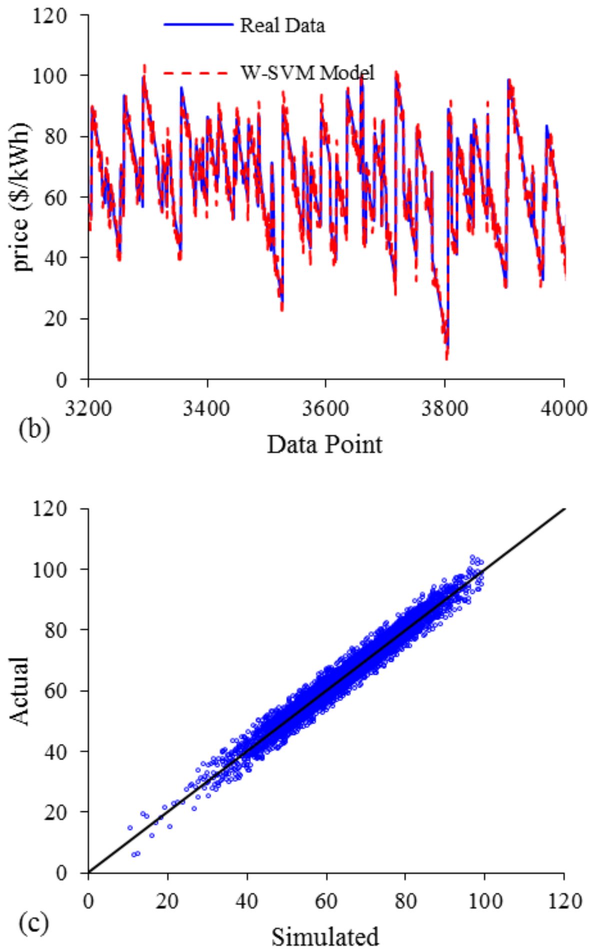


Fig. 1. The results of actual and W-SVM model for (a) train stage (b) test stage and (c) the corresponding scatter diagram in Spanish market system 2008

3.2 Iraqi market System case study

Figure 2 compares the theoretical value generated by the proposed model to the current market price. Eighty percent of the data set was used to train the proposed model. Figures 1-a and 1-b show how the model performed during training and testing compared to the true results. Figure 1-c is a scatter plot depicting the differences between the actual and modeled data along the x = y line. According to Table 1's evaluation indicators, the proposed model does a decent job of predicting prices in this system. As a result, the values of the evaluation indices MAPE, MAE, and RMSE during the test phase are respectively 2.59, 3.79, and 4.17, while the values of MAPE, MAE, and RMSE in this setup, during the training phase are equal to 2.92, 3.85 and 4.55.

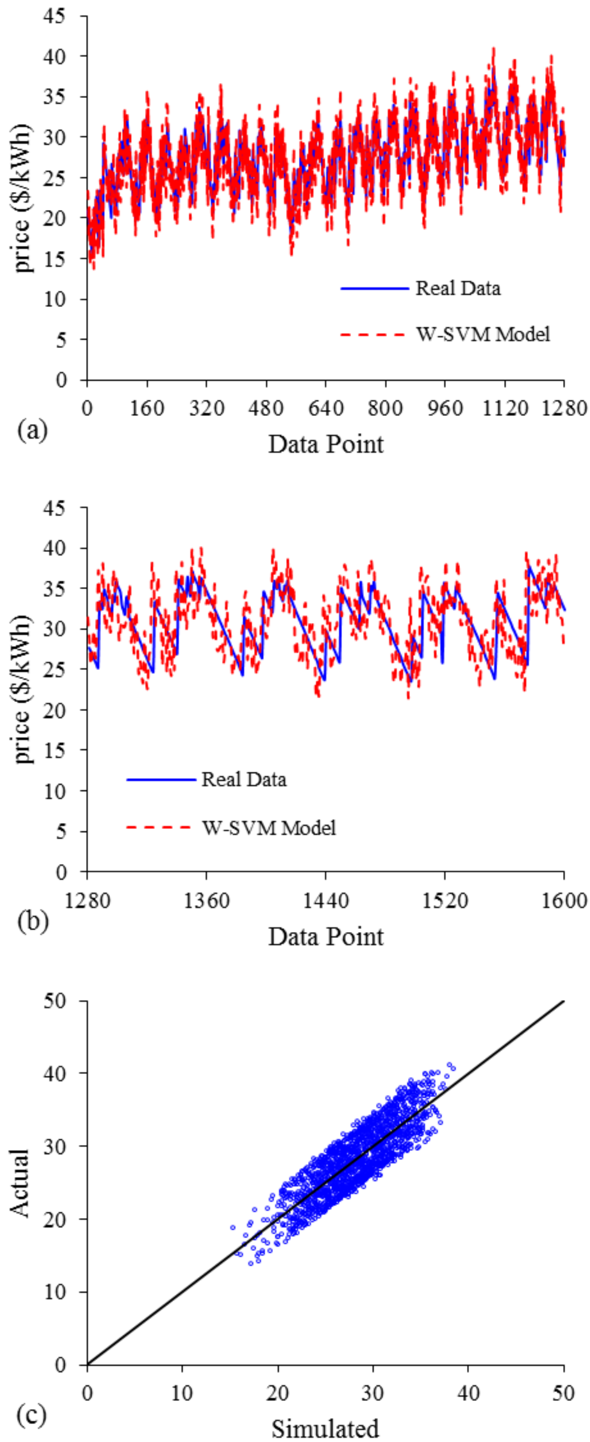


Fig. 2. The results of actual and W-SVM model for (a) train stage (b) test stage and (c) the corresponding scatter diagram in Iraqi market system 2018

Table 1. Hybrid W-SVM model performance in Spanish and Iraqi market system

State	Market System	Efficiency criteria		
		MAPE	MAE	RMSE
Train	Spanish	2.22	3.12	4.01
Test		2.76	3.71	4.32
Train	Iraqi	2.59	3.79	4.17
Test		2.92	3.85	4.55

4. Conclusions

As a result of the transformation of the electricity market from a state monopoly market to a competitive market in which the price is determined by market forces, modeling and forecasting the electricity price is completely risky, and due to the unpredictability of the electricity price determined by the competitive market, it is of particular importance for electricity market operators. It has been uncovered. To model and predict electricity prices in a competitive market, it is necessary to consider the volatile price-causing characteristics of this commodity, such as its ability to be stored, low elasticity, seasonality of demand, and the need for a continuous balance between supply and demand. This study aims to design and implement a support vector machine model with a wavelet transform function to explain and predict the short-term behavior of daily average cash prices in the Iraqi electricity market and global markets. The simulation results demonstrate that this combined model is superior to other available methods in terms of its predictive ability. In addition, the obtained results demonstrate the success of the electoral model in sorting data partitioned by wavelet transform. In addition, to overcome the irregular and nonlinear behavior of the input data, based on the variation in frequency and amplitude, it was performed exceptionally well, as evidenced by the graphs and tables.

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