Available online at sjuoz.uoz.edu.krd

Science Journal of University of Zakho

Vol. 5, No. 2, pp. 221 –227, June-2017

journals.uoz.edu.krd

p-ISSN: 2410-7549
e-ISSN: 2414-6943

FORECASTING THE ELECTRIC ENERGY SUPPLY IN DUHOK PROVINCE USING PROPOSED METHODS BASED ON WAVELET ANALYSIS AND SARIMA METHODS

Qais Mustafa Abdulqader

Dept. Information Technology, Zakho Technical Institute, University of Duhok Polytechnic, Kurdistan Region, Iraq - qais.mustafa@dpu.edu.krd

Received: Dec. 2016 / Accepted: May 2017 / Published: Jun. 2017 ***https://doi.org/10.25271/2017.5.2.372***

ABSTRACT:
Many applications have been done in the field of using wavelet analysis for time series analysis. In this study, we used the quarterly data of Electric Energy Supply in Duhok Province-Iraq in Megawatt which represents a sample size (46) observations during the period 2004 and 2015.we aim to describe how wavelet de-noising can be used in time series forecasting and improve the forecasting quality through presenting some proposed methods based on wavelet analysis and SARIMA method and applying on real data and make comparison between methods depending on some statistical criteria.Results from the analysis showed the superiority of the three proposed methods and showed that we can get more information from a series when using Wavelet-SARIMA method and this leads to enhance the classical SARIMA model in forecasting. Furthermore, after many empirical experiments with many wavelet families, it has been found that Daubechies, Coiflets, Discrete Meyer(dmey) and Symlet wavelets are very suitable when denoising the data and out of these four wavelet families, the Daubechies and Discrete Meyer performed better.

KEYWORDS: SARIMA, Wavelet-SARIMA, De-noising, Time Series Forecasting, Thresholding.

1. INTRODUCTION

Electricity is one of the most powerful forces in our lives. Electric energy supply forecasting is critically important in operation of electricity system since it can provide supportive information to help the system work securely and efficiently. Moreover, good results in electric energy supply forecasting can help significantly improve the economic factors of the power network operation.

Wavelet analysis technique for time series could be a very good tool for electric energy forecasting, which plays a significant role in the planning of economic and safe process for methods of modern energy. The process of reducing the noise from the original data before analyzing the series is important to get an improvement when modeling and forecasting. The wavelet denoising method depending on wavelet with a threshold is a robust mathematical tactic to reducing the noise from the original data while keeping the most amount of energy data that explains the actual data (Mustafa, and Alzubaydi, 2013).

Many implementations have been done and proposed using wavelet analysis in time series. Yi et al. (2008) suggested a new model for Short Term Load Forecast STLF in the market for electricity. The model was formed of a simulation platform. The simulation results showed that the model can make a sensible accuracy of forecasting in STLF. Aggarwal et al. (2009) presented a joint Wavelet Transform WT and Multiple Linear Regression MLR based method for price profile forecasting in a single compromise real- time electricity markets. the study ended that the proposed method can be used for providing a forecast with a sensible degree of accuracy and will be most useful during on-peak hours and times of high volatility. Frimpong and Okyere (2010) have developed a forecast model to predict the consumption of monthly energy by using wavelet transform and radiate base work neural network. A criterion Mean Absolute Percentage Error MAPE of 7.94% was carried out when the forecast model was examined over a 60-month interval. Moreno - Chaparro, et al. (2011) have proposed an approach of forecasting for the monthly electricity for the National Interconnected System NIS of Colombia. The method pre-operation the time series by employing a Multi-resolution Analysis MRA and using Discrete Wavelet Transform DWT. The prediction was gained by combining the forecast trend with the estimated gained by the residual series combined with further components that removed from pre-operation. Ming, et al. (2011) used characteristic extraction representing rising trend, periodical waves, and stochastic series for the purpose of forecasting the monthly consumption of electric energy. The outcomes of the analysis showed that the suggested method is preferable than those classically used in terms of forecasting precision and anticipated risks. Avdakovic, et al. (2012) used the linear regression and wavelet transforms approach to assessing the relationship between the Gross Domestic Product GDP, variations of air temperature, and the consumption of the power. They showed that forecasting the GDP and seasonal air temperature index trends should be considered in mid and long-term forecasting and power system planning. Avdakovic, et al. (2013) applied the continuous wavelet transform CWT with Morlet wavelet for performing the analysis of the hourly load of an actual power system. The outcomes showed that this method of analyses can confer a better insight into the essential characteristics of the consumption and recognize the characteristic periods of the power system load difference over the previous years, which can be very motivating for power system designers.

Very recently, Li, et al. (2014) proposed a new method for load forecast, which combines wavelet transform and radical learning machine. Numerical testing showed that the suggested method can enhance the forecast performance with minimum computational cost by comparison with other methods. Khandelwal, et al (2015) suggested new approach tactically uses the unique strengths of Discrete Wavelet Transform DWT, Autoregressive Integrated Moving Average ARIMA, and Artificial Neural Network ANN for improving the forecasting accuracy. Results of the study showed that the new approach obtains superior forecasting accuracies for each series. Rana and Koprinska (2016) offered Advanced Wavelet Neural Network**s** AWNN method for monthly, daily and hourly data’s and showed that the new method can be used for forecasting of other time series for power systems implementations. Jakub and Jerzy (2016) presented a hybrid method for forecasting the energy demand based on DWT and ANN. The presented method showed that introduction of the DWT as a pre-operating tool for the ANN input can give better results of forecasting models.

The main objective of this paper is to describe how wavelet de-noising can be used in time series forecasting and show the ability to minimize the noise from the main data and enhancing the forecasting quality when applying some proposed methods on real data and comparing the efficiency of the main classical ARIMA method and wavelet de-noising methodology.

In this paper, two different methods were considered for building a suitable model through applying on Electric Energy Supply data. In the first method, the data is modeled using classical ARIMA methodology. In the second method, the data is modeled using some proposed methods based on wavelet analysis and SARIMA methods. Then, some performance measures were computed for each method and have used for evaluation and comparison. The remainder of this paper is prepared as the following: Section 2 gives the brief explanation of ARIMA model and wavelet analysis. Section 3 gives some explanations of wavelet de-noising. Section 4 deals with application and main results. In section 5, we present some conclusions.

2. BRIEF EXPLANATIONS OF ARIMA MODEL AND WAVELET ANALYSIS

2.1 ARIMA Model

ARIMA model has got very high interest in the scientific world. The model becomes popular by George Box, Gwilym Jenkins, and Gregory C. Reinsel in 1970s (George, et al., 2008). It is well-known as ARIMA(p,d,q) and can express as:

$$x_t = \sum_{i=1}^{p} \emptyset_i x_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

Where p is the order of the nonseasonal autoregressive, q is the order of the nonseasonal moving average, $\emptyset_i$ are called autoregressive coefficients, θ_j are moving average coefficients and ε_t is the random error. First or second order of differencing is used if the original data is non-stationary. Often time series data containing seasonal variations. Monthly data series often shows a seasonal period of 12 months while quarterly data series always present a period of 4 quarters. Seasonality can be determined by examining whether the autocorrelation function of the data series with a specified seasonal order is significantly different from zero. For instance, if the autocorrelation coefficient of a monthly data series with new data series formed by a lag of 4 months is not significantly different from 0, the quarterly data series does not have a seasonality of 4 months; if the autocorrelation coefficient is significantly different from 0, it is very likely this monthly data series has a seasonality of 4 months. A seasonal ARIMA model can be built for a data series with seasonality.

For a time series x_t, its seasonality can be eliminated after D orders of differencing with a period of S. If a further d orders of regular differencing is still needed to make the data series stationary, a seasonal ARIMA can be built for the data series as follows:

$$\emptyset_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D x_t = \theta_q(B)\Theta_Q(B^s)x_t \qquad (2)$$

where P is the number of seasonal autoregressive parameter, Q is the seasonal moving average order, s is the period length (in quarters in this study), and D denotes the number of differencing passes. Then, we can express the model as SARIMA. For detecting the suitable model, we will use the Autocorrelation Function ACF and Partial Autocorrelation Function PACF. The pattern of the ACF/PACF plot gives us an idea towards which model could be the best fit for doing prediction. Also, we will use the Portmanteau test (i;e. Box-Pierce test) for the randomness of time series. The process of building model includes the following steps; identifying model, estimating parameters, diagnosing, and forecasting. We refer the reader to (Makridakis, et al., 1998) for more details.

2.2 Wavelet Analysis

As a mathematical tool, wavelet analysis transforms the original signal (especially with time domain) into a varied domain for analysis and processing. This tool is very proper for the non-stationary data, (i.e. mean and autocorrelation of the signal are not stable over time) and for this reason, most of the time series data is not stationary, that is why we used the wavelet transform (Al Wadia and Ismail, 2011). First, we look the Fourier transform, which decomposing the signals into sum of cyclical basis of indefinite lengths ($e^{jw(t)} = \cos(wt) + j\sin(wt)$) and has the ability to transform the domain of the signal from time to frequency and vice versa. The formula of the Fourier transform is:

$$X(f) = \int_{-\infty}^{+\infty} x(t)e^{-jw(t)}dt \qquad (3)$$

Where X(f) represents the Fourier transform of the signal x(t). The Fourier transform is basically an integral over time. Thus, we miss all information that varies with time. Thus, the formula becomes inactive for signal varies over time because it provides for us the information of frequency content. This leads to why the Fourier Transform expanded and modified to Gabor`s adaptation and called the Short-Time Fourier Transform STFT. It is expressed as:

$$STFT_X^{(W)}(t`, f) = \int_t^{\infty} \left[x(t).w^*(t-t`)\right].e^{-2\pi ft}dt \qquad (4)$$

Here, t` represents the shift factor, w(t) is the function of the window, and * is the complex joint. The STFT can give us a settlement of sorts between time and frequency information. The drawback here is that the accuracy is restricted by the size and shape of the window. For example, using many time pauses would give good time resolution but the very shortened time of each window would not give us perfect frequency resolution, especially for signals of lower frequencies (Fugal, 2009). The frequency component of a signal at a certain time cannot properly be specified. This is due to the Heisenberg`s uncertainty principle, which states that one cannot obtain simultaneous time and frequency Resolution (Gencay et al., 2002). For more details, we refer the reader to (Hubbard, 1996). This lack was overcome by the evolution of the wavelet transformation. Wavelet transforms let us variable-size windows. We can employ long time durations for more precise lower frequencies information and shorter intervals (allowing us to get more precise time information) for the higher frequencies (Fugal, 2009). The wavelet transform is expressed as follows:

$$\Psi_*^{\psi}(x,s) = \int x(t).\psi_{\tau,s}^*(t)d(t) \qquad (5)$$

and:

$$\psi_{\tau,s}^* = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \qquad (6)$$

Where s is called the binary dilation or scale variable and τ is the binary position or translation variable. When putting this description in equation (3) gives the definition of the CWT:

$$CWT_x^{\psi}(\tau,s) = \frac{1}{\sqrt{s}}\int x(t).\psi\left(\frac{t-\tau}{s}\right)d(t) \qquad (7)$$

From equation 7, the transformed signal is a function of both variables, τ and s the translation and scale parameters respectively. The translation τ is proportionate to the time information and the scale s, is proportionate to the frequency information. To find the constitutive wavelets of the signal, the coefficients must be multiplied by the relevant transformation of the mother wavelet (Misiti, et al., 1996).

For transforming wavelet to be calculated by using computers, it should use discrete quantities for the data. A continuous signal can be sampled thus a value is recorded after a discrete time duration. The DWT provides enough information for the analysis and composition of a signal but is useful, much more efficient. Discrete Wavelet analysis can be computed using the idea of filter banks. Filters of various cut-off frequencies resolve the signal at various scales. Resolution is varied by the filtering; the scale is varied by up-sampling and down-sampling. If a signal is put via two filters: a high-pass filter keeps high-frequency information and loses low-frequency information while a low-pass filter keeps low-frequency information and loses high-frequency information. Then the signal is decomposed into two parts effectively, high-frequency represents a detailed part, and low-frequency represents an approximation part. The sub signal created from the low filter will have the highest frequency equivalent to half that of the original. Depending on Nyquist sampling, this variation in frequency domain means that only half of the filtered samples need to be kept to perfectly rebuild the signal (i.e.; half of the samples are excessive). In other words, this means that downsampling can be applied to eliminate every second sample. The scale has now been multipled. The resolution has also been varied; obtaining better frequency resolution and reducing the time resolution is because of the filtering with down sampling. The approximation sub-signal can then be set via a filter bank, and this is renewed until the required level of decomposition has been accomplished. The DWT is obtained by combining the coefficients of the final approximation sub signal and the detail sub-signals.

The overall filtration procedure has the effect of separating out smoother and smoother detail, if all the details are up-sampled and added together then the main signal must be reduplicating. Employing a further analogy from Hubbard (Hubbard, 1996). This decomposition is like resolving the ratio 87/7 into parts of increasing detail, it means: 87 / 7 = 10 + 2 + 0.4 + 0.02 + 0.008 + 0. 0005. The detailed parts can then be built again to form 12.4285 which is close to the original number 87/7.

3. BRIEF INTRODUCTION TO WAVELET BASED DENOISING

Wavelet denoising procedure tries to eliminate the noise existent in the signal while preserving the signal features, regardless of its frequency content. The major idea of the wavelet denoising to get the perfect components of the signal from the noisy signal needs the estimation of the noise level. The estimated noise level is applied to threshold the small coefficient supposed as noise (Misiti, et al., 1996, Ergen, 2012). It is not easy to model the signal because of the actual and nonstationary of the noise infecting it. Despite that, if the noise assumed as stationary, then we can represent an empirically recorded signal that is corrupted by additive noise as:

$$s(i) = x(i) + \sigma e(i) \qquad i = 0,1,2,\ldots,n-1 \qquad (8)$$

Where s(i) is a noisy signal, x(i) is noise free real signal and e(i) are independent normal random variables and σ is the density of the noise in s(i). The noise, in general, is modeled as stationary independent zero-mean white Gaussian variables. When this model is applied, the objective of noise elimination is to rebuild the original signal x(i) from a finite set of s(i) values without assuming a construction for the signal.

The steps of the signal denoising based on DWT can be summarized as; decomposition of the signal, thresholding, and reconstruction of the signal which is in a practical manner reduced from noise (Burrus et al., 1998). The procedure is expressed in Figure.1

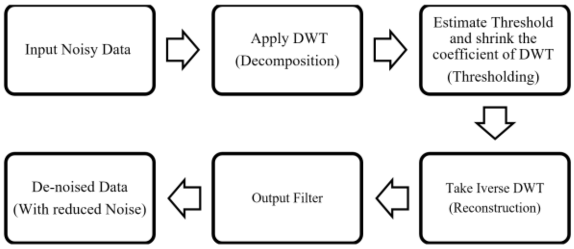

Figure 1. Diagram of data de-noising using DWT.

3.1 Threshold Selection

The procedure of Threshold selection is important to which is directly influence the quality of output denoised signal. There are several familiar methods used for threshold estimation. Some of them are discussed here briefly. In this paper, the performance of three well-known criterion threshold estimation methods are investigated for electric energy supply data in Duhok Province - Iraq contaminated by white Gaussian noise. The influence of wavelet decomposition level is also studied. These three methods are briefly described as follows (Cascio, 2007, Anestis, et al., 2001, Pallavi and Raskar, 2015):

3.1.1 Fixed Form: It is also called Universal Threshold and is defined by the following formula:

$$\delta^{(FT)} = \hat{\sigma}_{(MAD)}\sqrt{2\log(N)} \qquad (9)$$

Where (N) represents the number of wavelet coefficients in each level, $\hat{\sigma}_{(MAD)}$ is the estimate of the noise standard deviation and can be gained through applying a median absolute deviation (MAD) estimator to the N/2 wavelet coefficients at the first level of decomposition, merging a scale factor equal to (0.6745).

3.1.2 Minimax: Threshold technique proposed by Donoho (1995) to improve the Fixed Form threshold and the conception is to find an estimator $\hat{f}$ that gets the lowest of maximum risk, which means:

$$\hat{R}(F) = \inf_{\hat{f},\ f\in\hat{R}(F)} \sup R(\hat{f}, f) \qquad (10)$$

Where:

$$R(\hat{f}, f) = \frac{1}{N}\sum_{i=1}^{N} E\left[\hat{f} - f\right]^2 \qquad (11)$$

Where f=f(xi) and $\hat{f} = \hat{f}(xi)$, represents the vectors of real and estimated sample values. This estimator is the option that recognizes the minimum of the maximum Mean Square Error MSE gained for the worst function in each set.

3.1.3 Rigorous SURE: This threshold describes a scheme that employs a threshARGMINold value λ_j at each resolution level j of the wavelet coefficients. The Rigorous SURE threshold denoising process is also known as SURE Shrink and employs the Stein's Unbiased Risk Estimate criterion to obtain an unbiased estimate. The threshold is computed as follows:

$$\lambda_{SURE} = \mathrm{argmin}_{0<\lambda<\lambda\ UNI}\mathrm{SURE}\left(\lambda, \frac{S(a,b)}{\sigma}\right) \qquad (12)$$

Where SURE ( ) is defined as:

$$\mathrm{SURE}(\lambda; X) = n - 2 \clubsuit \{i: |X_i| \le \lambda\} + [\min(|X_i|, \lambda)]^2 \qquad (13)$$

and ♣ represents the cardinality of the set $\{i: |X_i| \leq \lambda\}$. Note that for coefficients of discrete wavelet the variable X is varied to $\frac{S(a,b)}{\sigma}$.

In accordance with estimating the threshold of a given level, wavelet coefficients of that level would be either hard or soft threshold. Hard thresholding represents the usual procedure of setting to zero the elements whose absolute values are lower than the threshold. Soft thresholding is an expansion of hard thresholding, first set to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients to zero. The hard procedure produces discontinuities, while the soft procedure does not (Misiti, et al., 1996). It was concluded in (Bruce and Gao, 1996) that soft threshold has a smaller variance than the hard threshold. In this paper, we only focus at soft thresholding for enhancing the ARIMA model of the data set. Two performance measures representing the Root Mean Squared Error RMSE and Akaike`s Information Criterion AIC are used to evaluate the performance of all denoising algorithms and thresholding basics in denoising the electric energy supply signals. The two measures can be described respectively using following expression (Vijay and Anil, 2013, Yaffee and McGee, 1999):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x - x_e)_i^2}{n - k}} \qquad (14)$$

$$\mathrm{AIC} = \ln\sigma_e^2 + \frac{2k}{n} \qquad (15)$$

Where n indicates the length of the signal or sample size, x is the original signal, x_e represents the estimated signal gained from the denoised wavelet coefficients and k denotes the number of estimated parameters of the model.

3.2 Classical ARIMA method and proposed methods

The process of building models using traditional ARIMA method and proposed methods were discussed here, as presented in Figure 2. Concerning the first method, the noisy data is modelled by applying the Box - Jenkins methodology. In proposed methods, the process of wavelet denoising based on DWT were given and used through smoothing and filtering the time series data using a set of wavelet filters with some familiar threshold estimation methods such as Fixed Form, Minimax, and Rigorous SURE thresholding. The filtered series are modelled, as in the traditional method and we put it as improved model for forecasting.

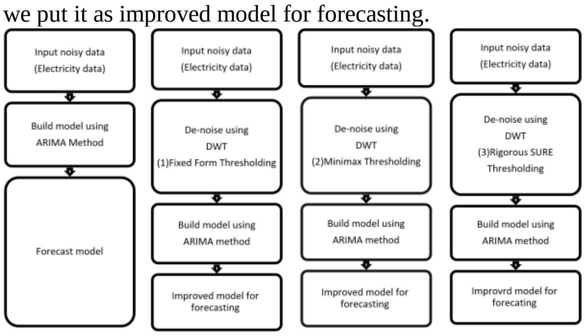

Figure 2. Building models using classical ARIMA method and proposed methods.

4. APPLICATION AND MAIN RESULTS

4.1 Application using classical ARIMA method

The actual values of the quarterly Electric Energy Supply (megawatt) in Duhok-Province were selected as shown in figure (3). The data represents sample size 46 observations during the period 2004 and 2015. The source of the data is obtained from the General Directorate of Electric Power in Duhok Province – Iraq. Figure (4) from the left to the right side represents the ACF and PACF of the series. The ACF plot represent

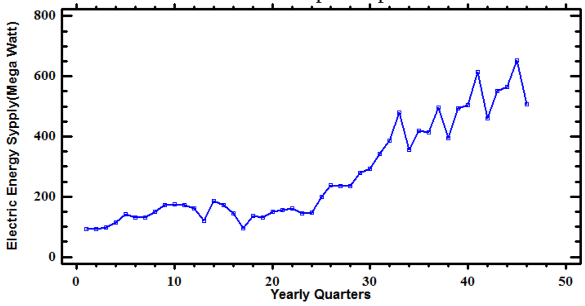

Figure 3. The quarterly data of Electric Energy Supply in Dohuk Province-Iraq in Mega Watts during the period 2004 and 2015.

A bar chart of the correlation coefficients between a series and lags of itself. The PACF plot represents the partial correlation coefficients between the series and lags of itself.

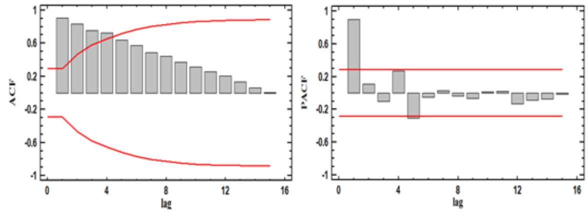

Figure 4. ACF and PACF of quarterly electric supply in Duhok Province during the period 2004 and 2015.

Figure 3 obviously exhibits upward increasing trend with features of seasonality and suggests that the current time series is non-stationary. From Figure 4, we can observe that the values of the ACF are gradually declining from a first - order autocorrelation coefficient to the end. The computed Portmanteau test of Box-Pierce with fifteen lags takes a value of 190.67 (p-value = 0.00), which is highly significant, confirming the autocorrelation pattern. The PACF shows a large peak at lag 1 with a rapid decline thereafter. We will first take a seasonal difference. The seasonally differenced data also appeared that the series is still nonstationary, and so we took an extra first difference of non-seasonal, as presented in Figure 5 and 6 respectively.

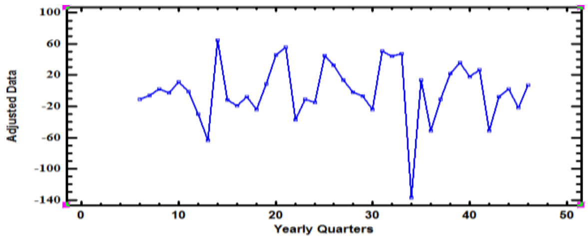

Figure 5. Double-differenced (seasonal and non-seasonal) of Electric Energy Supply

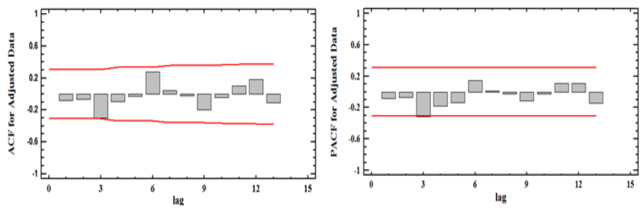

Figure 6. The values of ACF and PACF of double differenced (seasonal and non-seasonal) of Electric Energy data.

After obtaining stationarity, we proceed to fit an SARIMA model to the doubled difference of the series. We apply the two performance criteria; RMSE and AIC mentioned in theoretical part to select the suitable model order. Table1 presents different models of SARIMA specifications and the estimated criteria values.

Table 1. SARIMA model comparison using criteria values

Models	RMSE	AIC
SARIMA (1,1,1)(2,1,2)4	**30.2813**	**7.0819**
SARIMA(0,1,1)(2,1,2)4	32.1985	7.1612
SARIMA(1,1,0)(2,1,2)4	32.2086	7.1618

It is clear from table1 that, both performance criteria RMSE and AIC selected SARIMA(1,1,1)(2,1,2)4 model which having the smallest values of criteria compared with the others. Therefore, we conclude that the suitable and appropriate model is SARIMA(1,1,1)(2,1,2)4. The estimated model is presented in Table 2.

Table 2. Estimation of SARIMA(1,1,1)(2,1,2)4

Parameters	Estimates	Standard Error	t-ratio	P-value
AR(1)	0.6829	0.1304	5.2381	0.000008
MA(1)	1.0466	0.007	149.821	0
SAR(1)	0.5507	0.1608	3.4249	0.0016
SAR(2)	-0.7217	0.1366	-5.2822	0.000007
SMA(1)	0.6589	0.1287	5.1204	0.000011
SMA(2)	-1.0483	0.0672	-15.5943	0

After obtaining the estimation of the SARIMA(1,1,1)(2,1,2)4 model, we have to check for obtaining randomness. Figure 7 presents the ACF and PACF of residuals using SARIMA(1,1,1)(2,1,2)4 on series data.

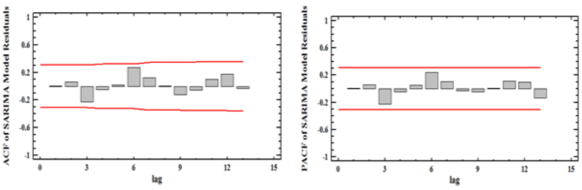

Figure 7. ACF and PACF of residuals using SARIMA(1,1,1)(2,1,2)4 on series data.

Through looking at Figure 7, none of the autocorrelations coefficients of ACF and PACF are significant, which strongly suggesting that the time series may well is completely random (i.e.; white noise). Also, we did a test for randomness of residuals using a Portmanteau test (or Box-Pierce test), which has been mentioned in the theoretical part. The value of the test statistics was (8.3234) and the P-value was (0.3049) indicating that we cannot reject the hypothesis that the series is random at the 95% or higher confidence level.

4.2 Application of proposed methods

The quarterly data of Electric Energy Supply was modeled using classical ARIMA methodology as SARIMA(1,1,1)x(2,1,2)4.The parameters were selected after careful modeling and fitting and depending on the performances criteria mentioned theoretical part. The performance measures RMSE and AIC of the above model were computed. Figure 8 presents wavelet analysis using Daubechies wavelet of order 6 with five levels multiresolution for the Electric Energy Supply for 46 sequential observations, where s represents the signal and it is equal to the sum of its approximation and of its fine details, a5 is approximation at level 5 and d5; d4; d3; d2; d1 are the details at level 5,4,3,2 and 1.

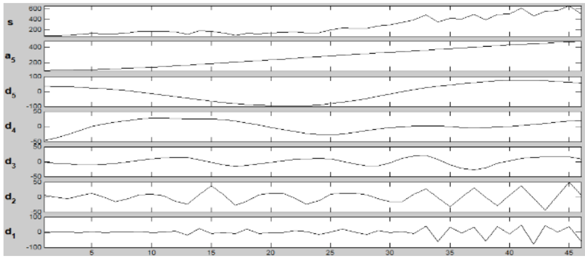
Figure 8. Five levels multiresolution wavelet analysis using Daubechies wavelet of order 6 wavelet for the quarterly data of Electric Energy Supply in Dohuk Province-Iraq.

The original or noisy data of Electric Energy Supply denoised using wavelet denoising procedure mentioned in theoretical part (using MATLAB software, version 2013) with four different wavelet families. It is important here to say that after many empirical experiments with many wavelet families, it has been found that these wavelets perform better than others in terms of denoising the Electric data and they are (Fugal, 2009):

1- Daubechies wavelet of order 3 and 6.
2- Coiflets wavelet of order 4.
3- Discrete Meyer (dmey) wavelet.
4- Symlet wavelet of order 7.

The shape of the above wavelet families presented in Figure 9.

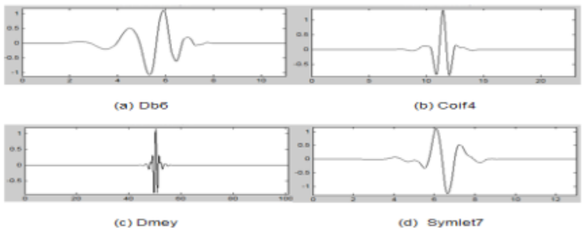

Figure 9. Shapes of different wavelets: (a) Daubechies of order 6, (b) Coiflet of order 4, (c) Discrete Meyer, (d) Symlet of order 7.

The three proposed methods were applied to data through the following procedure: The threshold selection for de-noising was depending on Fixed Form, Minimax, and Rigorous SURE as mentioned in theoretical part. The data was first analyzed for five multi-resolution levels for the selected wavelet, and denoised using different thresholds with soft thresholding. Then, the new series were modeled using SARIMA method and forecasting criteria were calculated and compared with those in the first method mentioned before. Table 3 summarizes the performance of the two criteria for the original data model using SARIMA method and proposed methods.

From Table 3 one may note that the best estimation model for the original Electric data after careful modeling and fitting was SARIMA(1,1,1)(2,1,2)4. However, when proposed methods based on wavelet de-noising applied on the original data the forecasting errors have reduced and the new models have been improved depending on the performance measures. Comparing SARIMA method with the proposed method(1) we can see that the reduction is maximum when applying Fixed Form thresholding and using Discrete Meyer wavelet (i.e.; note from the Table 3 good reduction in RMSE and AIC from 30.281 to 28.095 and from 7.082 to 6.932, respectively).

Table 3. The performance measures for the original Electric data model using classical SARIMA method and proposed methods.

Method	Kind	RMSE	AIC
Classical SARIMA Method Original data	SARIMA(1,1,1)(2,1,2)4	30.281	7.082
Proposed Method(1)	Daubechies(6)	28.401	6.954
Fixed Form Thresholding	Coiflet(4)	28.62	6.97
De-noised data	Discrete Meyer(dmey)	**28.095**	**6.932**
	Symlet(7)	28.72	6.98
Proposed Method(2)	Daubechies(6)	29.291	7.01
Minimax Thresholding	Coiflet(4)	29.38	7.02
De-noised data	Discrete Meyer(dmey)	**28.916**	**6.99**
	Symlet(7)	29.45	7.03
Proposed Method(3)	Daubechies(3)	**29.184**	**7.008**
Rigorous SURE Thresholding	Coiflet(4)	30.418	7.03
De-noised data	Discrete Meyer(dmey)	30.066	7.068
	Symlet(7)	29.808	7.05

Table 4. Forecast values of Electric Energy Supply data using classical SARIMA(1,1,1)(2,1,2)4 and the proposed methods

Period	Classical SARIMA Method	Proposed Method(1)	Proposed Method(2)	Proposed Method(3)
Quarters	SARIMA(1,1,1)(2,1,2)4	Fixed Form Thresholding	Minimax Thresholding	Rigorous SURE Thresholding
	Original Data	Discrete Meyer(dmey)	Discrete Meyer(dmey)	Daubechies(3)
	Forecast	Forecast	Forecast	Forecast
2015 Q3	596.514	597.975	597.109	591.559
2015 Q4	610.634	612.155	612.298	606.11
2016 Q1	696.381	691.519	694.429	690.331
2016 Q2	549.193	551.281	552.685	550.554
2016 Q3	641.633	640.177	643.087	635.51
2016 Q4	658.069	657.013	660.525	651.723
2017 Q1	748.907	742.125	747.916	740.768
2017 Q2	596.591	602.751	603.151	596.805
2017 Q3	692.372	691.276	695.763	684.405
2017 Q4	709.723	709.807	714.274	701.747

Comparing SARIMA model with the proposed method (2) we can see that the reduction is maximum when applying Minimax thresholding and using Discrete Meyer wavelet (note from the Table 3 the good reduction in RMSE and AIC from 30.281 to 28.916 and from 7.082 to 6.989, respectively). Finally, Comparing SARIMA model with the proposed method (3) we can observe that the reduction is maximum when the data was Rigorous SURE thresholding using Daubechies wavelet of order 3 (note from the table (3) the good reduction in RMSE and AIC from 30.281 to 29.184 and from 7.082 to 7.008, respectively). The forecast values of classical model and proposed methods are presented in Table 4.

5. CONCLUSIONS

This study leads to the following conclusions:

1- The suitable model using classical method was SARIMA(1,1,1)(2,1,2)4.

2- Further information could be gained from a series when applying wavelet denoising method and this leads to enhance the classical method.

3- The three proposed methods were better than classical SARIMA method for forecasting the Electric Energy Supply data depending on performance measures and among them, the proposed method (1) depending on Fixed Form Thresholding was the best one.

4- It was found that Daubechies, Coiflets, Discrete Meyer(dmey) and Symlet wavelets are very suitable when denoising the Electric Energy Supply data and out of these wavelet families, the Daubechies and Discrete Meyer performed better.

REFERENCES

Aggarwal, S. K., Saini, L. M., and Kumar, A. (2009). Electricity price forecasting using Wavelet-domain and Time domain features in a Regression based technique. *International Journal of Recent Trends in Engineering*, 2, 33-37.

Al Wadia, S., and Ismail, M., T. (2011). Selecting wavelet transforms model in forecasting financial time series data based on ARIMA model. *Applied Mathematical Sciences*, 5, 315-326.

Anestis, A., Jeremie, B., and Theofanis, S. (2001). Wavelet Estimators in nonparametric regression: A comparative simulation study. *Journal of Statistical Software*, 6, 1-83.

Avdakovic, S., Ademovic, A., and Nuhanovic, A. (2012). Insight into the properties of the UK power consumption using a linear regression and wavelet transform approach. *Elektrotehniški Vestnik/Electrotechnical Review*. 79, 278-283.

Avdakovic, S., Nuhanovic, A., Kusljugic, M., Becirovic, E., and, Turkovic, E. (2013). Wavelet multiscale analysis of a power system load variance. *Turkish Journal of Electrical Engineering & Computer Sciences*. 21, 1035-1043.

Bruce, A. G., and Gao, H. Y. (1996). Understanding waveshrik: Variance and Bias Estimation. *Journal of Biometrical*, 83, 727-745.

Burrus, C. S., Gopinath, R. A., and Gao, H. (1998). Introduction to wavelets and wavelet transform, New Jersey, Prentice whole, Upper Saddle River.

Cascio I. L. (2007). Wavelet analysis and de-noising: New tools for economists, London, Queen Marry Press.

Ergen, B. (2012). Signal and image denoising using wavelet transform. Advances in Wavelet theory and their applications in engineering, physics, and technology. InTech publisher.

Frimpong, E., A., and Okyere, P., Y. (2010). Monthly energy consumption forecasting using wavelet analysis and radial basis function neural network, *Journal of Science and Technology*, 30, 157-164.

Fugal, D. L. (2009). Conceptual Wavelets in digital signal processing. San Diego, California, space and signals Technical Publishing, LLC.

Gencay, R., Selcuk, F. and Whitcher, B. (2002). An introduction to wavelets and other filtering methods in finance and economics, San Diego, California, Academic Press.

George E. P. B., Gwillym, M. J., and Gregory, C. R. (2008). Time series analysis: Forecasting and control, (4th ed.). John Wiley & Sons, INC.

Hubbard, B., B. (1996). The world according to wavelets: The story of a mathematical technique in the making, Wellesley, Massachusetts, A.K. Peters press L.T.D.

Jakub, J., and Jerzy, M. (2016). Day ahead electric power load forecasting by WT-ANN. *Przeglad Elektrotechniczny*. 4, 152-154.

Khandelwal, I., Adhikari, R., and Verma, G. (2015). Time series forecasting using hybrid ARIMA and ANN models based on

DWT Decomposition. *Procedia Computer Science*. 48, 173–179.
Li, S., Wang, P., and Goe, L. (2014). Electric Load Forecasting Using Wavelet Transform and Extreme Learning Machine. *Proceedings of European Symposium on Artificial Neural Networks, Computational Intelligence, and Machine Learning.* Bruges (Belgium), 23-25 April.
Makridakis, S., Wheelwright S. C., and Hyndman R. J. (1998). Forecasting: Methods and applications. (3rd ed.). John Wiley & Sons, INC.
Meng, M., Niu, D., and Sun, W. (2011). Forecasting monthly electric energy consumption using feature extraction. *Energies*. 4, 1495-1507.
Misiti, M., Misiti, Y., Oppenheim, G., and Poggi, J., M. (1996). Wavelet toolbox user`s guide, Version1, USA, The Math Works, Inc.
Moreno-Chaparro, C., Salcedo-Lagos, J., Rivas, E. y., and Orjuela-Canon, A. (2011). A method for the monthly electricity demand to forecast in Colombia based on wavelet analysis and a nonlinear autoregressive model. *Ingeniería*, 16, 94 – 106.
Mustafa, Q., and Alzubaydi, T., H. (2013). Comparing the Box-Jenkins models before and after the wavelet filtering in terms of reducing the orders with application, *Journal of Concrete and Applicable Mathematics*, USA, Eudox Press, LCC, 11, 190-198.
Pallavi, L. P., and Raskar, V. P. (2015). Image de-noising with wavelet thresholding method for different level of decomposition. *International Journal of Engineering Research and General Science*, 3, 1092-1099.
Rana, M., and Koprinska, I. (2016). Forecasting Electricity Load with Advanced Wavelet Neural Networks. *Neurocomputing*, 182, 118-132.
Vijay, S. C., and Anil, K. T. (2013). Design methodology of a new wavelet basis function for fetal phono cardiographic signals. *The Scientific World Journal*, 2013, 1-12.
Yaffee, R. and McGee, M. (1999). Introduction to time series analysis and forecasting: With applications of SAS and SPSS. New York, Academic Press.
Yi, M., M., Linn, K., S., and Kyaw, M. (2008). Implementation of Neural Network Based Electricity Load Forecasting. *World Academy of Science, Engineering, and Technology*, 42, 381-386.

پێشبینکرنا کەرەستەپێدانێ یا وزەی کارەبایێ ل پارێزگەها دهوکێ ب کارئینانا رێکێن پشنیارکری ل سەر پشت بەست ب شلوڤەکرنا پێلا بچیك ل گەل رێکا SARIMA

کورتیا لێکولینێ:

گەلەك جێ بەجێکرن هاتینە ئەنجامدان د بوارێ شلوڤەکرنا پێلا بچیك بۆ شلوڤەکرنا زنجیرێن کاتی.دڤێ ڤەکولینێ دا داتاییێن چارێك سالانە هاتنە ب کارئینان یێن کەرەستەپێدانێ یا وزەی کارەبایی ل پارێزگەها دهوکێ – عیراق ب (مێگاواتی) ئەو ژی بریتی یە ژ بژاردەیەکێ ب قەبارە ٤٦ دانە د ناڤ ماوا سالێن د ناڤبەرا ٢٠٠٤ و ٢٠١٥. ب مەرەما باسکرنا چونیەتیا پێلا بچیك د کێمکرنا (هەڵە)یێ و ب کارئینانا وێ د پێشبینکرنا زنجیرێن کاتی و چاککرنا کوالیتا پێشبینکرنێ ئەو ژی ب رێکا پێشکێشکرنا چەند رێکێن پشنیارکری ل سەر بنەمایا شلوڤەکرنا پێلا بچیك و رێکین SARIMA و جێبەجێکرنا وان رێکان ل سەر داتاییێن راستەقینە و هەروەسا بەراوردی د ناڤ بەرا وان رێکان دا بهێتە کرن ل سەر ینەماییێن چەند پێڤەرێن ئاماری. ئەنجامێن شلوڤەکرنێ دیار کرن باڵادەستی هەر سێ رێکێن پشنیارکری و هەر وەسا دیار کر کو پتر پێزانین دشێن بهێنە ب دەستڤە ئینان ژ زنجیرێ ل دەمێ ب کارئینانا پێلا بچیك ل گەل رێکا SARIMA ئەو ژی خۆ ڤەدکێشیت بو چاککرنا مودێلا SARIMA یا کلاسیکی بۆ پێشبنکرنێ.ژ بلی وێ چەندێ و پشتی گەلەك هەوڵدانێن تاقیکرنێ ئەوێن هاتین ئەنجامدان ل گەل گەلەك خێزانێن پێلا بچیك وەسا دیاربی کو پێلێن یچیك (Dauchies, Coiflets, Discrete Meyer(dmey), Symlets) گەلەك یێن گونجاینە ل دەمێ ژێبرنا (هەڵە)یێ ژ داتایا و ژ ناڤ وان چوار پێلێن بچیك کارێ دوو ژ وان ئەو ژی (Dauchies, Discrete Meyer (dmey)) یێ باشتر بی.

التنبؤ بتجهيز الطاقة الكهربائية في محافظة دهوك باستخدام طرق مقترحة بالإستناد إلى تحليل المويجة وطرق SARIMA

خلاصة البحث:

إن العديد من التطبيقات قد تم إنجازها في مجال تحليل المويجة في تحليل السلاسل الزمنية. في هذا البحث تم إستخدام بيانات ربع سنوية لتجهيز الطاقة الكهربائية في محافظة دهوك-العراق بالميكاوات والتي تمثل عينة حجمها ٤٦ مشاهدة خلال الفترة من ٢٠٠٤ و ٢٠١٥. إستهدفنا وصف قدرة المويجة في تقليل الضوضاء وإستخدامها في التنبؤ بالسلاسل الزمنية ومن ثم تحسين جودة التنبؤ و ذلك من خلال تقديم بعض من الطرق المقترحة بالإستناد إلى تحليل المويجة وطريقة SARIMA و تطبيقها على بيانات حقيقية وإجراء مقارنة بين الطرق بالإعتماد على بعض المعايير الإحصائية. أظهرت نتائج التحليل تفوق الطرق المقترحة الثلاثة وكذلك أظهرت أن المزيد من المعلومات يمكن الحصول عليها من خلال السلسلة الزمنية عند إستخدام المويجة مع طريقة SARIMA وهذا يؤدي إلى تحسين نموذج SARIMA التقليدي في التنبؤ.إضافةً إلى ذلك وبعد العديد من المحاولات التجريبية مع العديد من عائلات المويجة فقد تبين أن المويجات (Dauchies, Coiflets, Discrete Meyer(dmey) ,Symlets) مناسبة جداً عند إزالة الضوضاء من البيانات ومن بين هذه المويجات الأربعة كانت المويجتان (Daubechies, Discrete Meyer(dmey)) أدائهما أفضل.