Universidad Autónoma de Santo Domingo Energy Forecast

Felipe Llaugel[1,2]
Dennis Ridley[3,4]
Amparo Cespedes[1]

[1]*Universidad Autonoma de Santo Domingo*
[2]*Universidad Dominicana O&M*
[3]*Florida A&M University*
[4]*Florida State University*

fllaugel@udoym.edu.do; dridley@fsu.edu; acespedes09@uasd.edu.do

Abstract: Energy time series data for Universidad Autonoma de Santo Domingo is analyzed and forecast by the moving window spectral method to capture cyclical components and effects. The historical record is 217 months from March 2001 to March 2019. A model is fitted to 205 historical observations from March 2001 to March 2018. The forecast period is 12 months from April 2018 to March 2019. The two overlapping 12 actual and forecast months are compared.

1. INTRODUCTION

Forecasting energy consumption has been a subject of interest in many countries. Azadeh et al. (2008) conducted monthly energy forecasting in Iran. In Thailand, Panklib, et al. (2015) used a neural network model to compare performance with a multiple linear regression method. In Italy, Bianco et al., (2013) proposed multiple linear regression to predict the energy consumption with GDP and population as independent variables. Guo et al., (2018) tested the applicability of a new monthly electricity forecasting framework to predict energy consumption in china. The framework is based on a method of vector error correction and self-adaptive screening. The main benefit of this proposal is to address the problem of data types and data length by identifying the most influential input factor groups for the model.

Energy time series data for Universidad Autónoma de Santo Domingo (UASD) is analyzed and forecast by the moving window spectral method (mws) (Ngnepieba and Ridley, 2007; Ridley and Womer, 1981; Ridley, 1994, 2001, 2003; Ridley and Llaugel, 2000; Ridley and Ngnepieba, 2009) to capture cyclical components and effects. Data analysis and forecasting in the time domain is natural but it ignores the fact that time series may be made up of trend and cyclical components, and the components might be varying, growing and shrinking in different ways. The mws method divides the history into overlapping windows of length equal to the longest dominant cycle in the data.

Although the analyst is free to try different window lengths and thereby estimate and choose it empirically, these data are expected to contain at least a seasonal effect represented by a 12-month cycle. In that case the window length must be a whole multiple of 12. The mws method uses a fast Fourier transform (FFT) to decompose each window into cyclical components. Whereas the original data are represented in the time domain where they are indexed by time, the component cycles are represented in the complex frequency domain where they are indexed by frequency.

These components are assumed to be a set of correlated sequences. A complex function is fitted, separately by frequency, to each sequence of components by simple regression. Each component sequence is then extrapolated from the most recent sequence to the following sequence of values. The extrapolated sequences are then inverse transformed back to the time domain where they are interpreted in the normal way by the human observer. The historical record is 217 months from March 2001 to March 2019. A model is fitted to 205 historical observations from March 2001 to March 2018. The forecast period is 12 months from April 2018 to March 2019. The two overlapping 12 actual and forecast months are compared.

1.1. The University

In its main campus, UASD has 18 buildings that are important to energy consumption. During the period from September 2017 to September 2018, the average energy consumption throughout the campus was 1,389 MWh / month, with a maximum demand of 3.8 MW,

Twenty years ago, the University had fewer buildings. Many have been added over the years in accordance with economic possibilities. The most important buildings added are: The administrative tower, the high technology laboratories, and the central library. All of these have added greatly to the energy and power demand by the main campus.

One of the deficiencies of structural development in the Dominican Republic can be seen within UASD. New buildings are built without having been planned and because of that, the services that support the proper functioning of these are inadequate. Among these we can mention the electricity service. In order to provide electricity efficiently, the production must adapt to the demands of the current demand hour by hour. The lack of generating supply options, and flexibility, does not permit efficient scheduling.

Other deficiency factors are insufficient backup generating capacity in case of failure of a generator, and support elements such as underrated insulators and undersized conductors, etc. Under insulation can cause outages due to electrical faults. Undersized conductors cause excessive heat losses. Forecasting of power requirements are critical for the purpose of providing information to plan for future service requirement. In this paper we forecast energy consumption. The forecast energy consumption can be converted to power demand by dividing by the power factor which is known to be 0.9.

2. THE DATA

The historical record of monthly energy consumption in kilowatt hours (kwh) from March 2001 to March 2019 for Universidad Autónoma de Santo Domingo (UASD) is given in table 1. The data include consumption at the main campus of the University. Preliminary analysis of the data indicates some trend and seasonal variations (see Figure 1).

Table 1. University monthly energy consumption (in Kwh)

Energy Consumption													
Date	KWh	Date	KWh	Date	KWh	Date	KWh	Date	KWh	Date	KWh	Date	KWh
Mar-01	426,369	Oct-03	537,600	May-06	50,880	Dec-08	772,800	Jul-11	967,200	Feb-14	908,229	Sep-16	1,488,000
Apr-01	548,400	Nov-03	516,000	Jun-06	741,600	Jan-09	717,600	Aug-11	816,000	Mar-14	1,435,200	Oct-16	1,636,800
May-01	418,800	Dec-03	415,200	Jul-06	753,600	Feb-09	998,400	Sep-11	1,137,600	Apr-14	1,598,400	Nov-16	1,483,200
Jun-01	472,800	Jan-04	235,200	Aug-06	748,800	Mar-09	1,036,800	Oct-11	1,137,600	May-14	1,497,600	Dec-16	1,555,200
Jul-01	428,400	Feb-04	439,200	Sep-06	1,003,200	Apr-09	1,130,400	Nov-11	1,135,200	Jun-14	1,411,200	Jan-17	940,800
Aug-01	231,600	Mar-04	573,600	Oct-06	1,171,200	May-09	1,094,400	Dec-11	784,800	Jul-14	1,478,400	Feb-17	974,400
Sep-01	29,520	Apr-04	626,400	Nov-06	1,255,200	Jun-09	1,154,400	Jan-12	703,200	Aug-14	1,550,400	Mar-17	1,257,600
Oct-01	501,600	May-04	518,400	Dec-06	1,060,800	Jul-09	1,180,800	Feb-12	1,005,600	Sep-14	1,502,400	Apr-17	1,512,000
Nov-01	554,400	Jun-04	446,400	Jan-07	792,000	Aug-09	1,183,200	Mar-12	1,118,400	Oct-14	1,728,000	May-17	1,320,000
Dec-01	429,600	Jul-04	532,800	Feb-07	772,800	Sep-09	1,344,000	Apr-12	1,087,200	Nov-14	1,848,000	Jun-17	1,502,400
Jan-02	232,800	Aug-04	628,800	Mar-07	962,400	Oct-09	1,358,400	May-12	921,600	Dec-14	1,593,600	Jul-17	1,392,000
Feb-02	412,800	Sep-04	696,000	Apr-07	1,197,600	Nov-09	1,214,400	Jun-12	1,171,200	Jan-15	1,012,800	Aug-17	1,464,000
Mar-02	470,400	Oct-04	662,400	May-07	1,070,400	Dec-09	914,400	Jul-12	1,200,000	Feb-15	1,060,800	Sep-17	1,344,000
Apr-02	516,000	Nov-04	712,800	Jun-07	1,058,400	Jan-10	696,000	Aug-12	993,600	Mar-15	430,400	Oct-17	1,387,200
May-02	516,000	Dec-04	460,800	Jul-07	1,089,600	Feb-10	1,113,600	Sep-12	162,000	Apr-15	1,593,600	Nov-17	1,680,000
Jun-02	429,600	Jan-05	314,400	Aug-07	1,058,400	Mar-10	1,221,600	Oct-12	1,454,400	May-15	1,579,200	Dec-17	1,248,000
Jul-02	494,400	Feb-05	525,600	Sep-07	1,118,400	Apr-10	1,183,200	Nov-12	460,800	Jun-15	1,689,600	Jan-18	936,000
Aug-02	460,800	Mar-05	664,800	Oct-07	1,224,000	May-10	1,048,800	Dec-12	1,161,600	Jul-15	1,718,400	Feb-18	1,152,000
Sep-02	535,200	Apr-05	511,200	Nov-07	1,142,400	Jun-10	996,000	Jan-13	878,400	Aug-15	1,713,600	Mar-18	1,305,600
Oct-02	468,000	May-05	403,200	Dec-07	691,200	Jul-10	952,800	Feb-13	1,358,400	Sep-15	1,598,400	Apr-18	1,516,800
Nov-02	614,400	Jun-05	410,400	Jan-08	784,800	Aug-10	988,800	Mar-13	1,392,000	Oct-15	1,545,600	May-18	1,521,600
Dec-02	487,200	Jul-05	420,000	Feb-08	1,000,800	Sep-10	1,161,600	Apr-13	1,454,400	Nov-15	244,800	Jun-18	1,406,400
Jan-03	201,600	Aug-05	408,000	Mar-08	950,400	Oct-10	1,272,000	May-13	1,627,200	Dec-15	1,339,200	Jul-18	1,348,800
Feb-03	456,000	Sep-05	460,800	Apr-08	1,135,200	Nov-10	1,041,600	Jun-13	1,449,600	Jan-16	1,276,800	Aug-18	1,531,200
Mar-03	518,400	Oct-05	597,600	May-08	986,400	Dec-10	727,200	Jul-13	1,531,200	Feb-16	1,171,200	Sep-18	1,430,400
Apr-03	513,600	Nov-05	811,200	Jun-08	1,051,200	Jan-11	542,400	Aug-13	1,473,600	Mar-16	1,483,200	Oct-18	1,051,200
May-03	482,400	Dec-05	883,200	Jul-08	1,111,200	Feb-11	880,800	Sep-13	1,785,600	Apr-16	1,497,600	Nov-18	1,576,800
Jun-03	482,400	Jan-06	46,320	Aug-08	96,480	Mar-11	487,200	Oct-13	1,641,600	May-16	1,622,400	Dec-18	1,670,400
Jul-03	446,400	Feb-06	429,600	Sep-08	1,058,400	Apr-11	1,017,600	Nov-13	1,550,400	Jun-16	1,444,800	Jan-19	936,000
Aug-03	302,400	Mar-06	600,000	Oct-08	1,190,400	May-11	1,075,200	Dec-13	1,065,600	Jul-16	1,555,200	Feb-19	1,123,200
Sep-03	494,400	Apr-06	720,000	Nov-08	996,000	Jun-11	955,200	Jan-14	955,200	Aug-16	1,502,400	Mar-19	1,404,000

The summary statistics of the data are as follows:

```
Minimum            29.520
Maximum          1848.000
Mean              976.401
Standard dev.     434.288
Mean abs dev.     367.446
Auto correl.        0.753
Coeff of var.       0.445
MAD/S.              0.846
ChiSqr(7,5%)=14    39.653
```

The summary data for Table 1 shows the MAD/S =0.846 and is a little higher than the value of 0.8 for a normal distribution. The ChiSqr test statistic of 39.653 is greater than the theoretical ChiSqr value of 14. It does appear that the data are normally distributed. Nevertheless, the histogram (not shown) is symmetrical. That will enable the construction of prediction when it comes time to forecast future values.

3. THE MWS MODEL

Consider a stationary time series model where UASD is represented by y:

$$y(t) = \sum_{k=1}^{T} y(t-k)b(k) + \varepsilon(t), t = T+1, T+2, T+3, \ldots, \infty \tag{1}$$

where
$b(k)$= system parameter, coefficient of y lagged k time periods,
$\varepsilon(t)$ = an unobservable error term, a sequence of independent identically distributed normal random variables with mean 0 and variance $\sigma^{2,}$
T = window length.
The Cooley-Tukey (1965) complex FFT is used to estimate the spectral density for each window y(m-1+t), m =1,2,...,n-T+1 from

$$Y_m(\omega) = \sum_{t=1}^{T} y(m-1+t)\exp(-i\omega t), \qquad -\pi \le \omega \le \pi \tag{2a}$$

Where m is the window number and the index of the realization of a cycle at frequency ω and $i = \sqrt{-1}$.

That is, there are n-T+1 realization.

Likewise,

$$B(\omega) = \sum_{k=1}^{T} b(k)\exp(-i\omega k), \tag{2b}$$

the spectral density function of the impulse response function $b(k)$, is constant across windows, and

$$\in_m (\omega) = \sum_{t=1}^{T} \varepsilon(m-1+t)\exp(-i\omega t), \tag{2c}$$

the spectral density function of independent identically distributed time domain errors, is constant [Chatfield(1996, ch. 6)] across frequency.

4. THE MWS PARAMETERS

The MWS method generates two sets of parameter estimates, one in the frequency domain (Table 2) and one in the time domain (Table 3). All computations were made by a computer program [see Ridley (2002)]. Each line entry in Table 2 contains an estimate of the parameters $|\hat{B}(\omega)|$ which is the coefficient in a first order autoregressive model. The standard error of estimate for the parameters is S. The number of data points after first differencing is 205-1=204. The error degrees of freedom = n-T-1 = (204-12-1) =191. The t statistic for a 5% level of significance is approximately 2. The first entry corresponds to the zero frequency, that is, the non-periodic trend component. The t test statistic 1.004/0.00206 = 487.179 exceeds 2, so this component is significant at the 5% level. The next component corresponds to the cycle that repeats once every 12 months. It has a period of 12 months. That component, as well as all other components are significantly different from zero.

Each coefficient has a magnitude close to 1. The coefficient of the zero-frequency trend is 1.004. The cycles have fractional coefficients implying that those cycles are falling in magnitude over time. The coefficient of the dominant 12-month cycle is 0.956. The coefficient of the 2-month cycle is very close to 0.904.

Table 2. Frequency domain parameter estimate $|\widehat{B}(\omega)|$

FREQUENCY No.	PERIOD	PARAMETER ESTIMATES magnitude/shift	S	t
0	----	1.004	0.00206	487.179
1	12.0	0.956	0.02109	45.345
2	6.0	0.939	0.02462	38.148
3	4.0	0.908	0.02991	30.359
4	3.0	0.836	0.03924	21.298
5	2.4	0.882	0.03380	26.091
6	2.0	0.904	0.03037	29.772

After inverse transformation back to the time domain, the model parameter estimates are given in Table 3 and equation 3. The parameters are those of a distributed lag function. This is also an impulse response function.

$$y(t) = 0.407y(t-1) + 0.029y(t-2) + 0.011y(t-3) + \cdots + 0.912y(t-12) \quad (3)$$

Table 3. Impulse response $\widehat{b}(t)$

Lag	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
$\hat{b}(t)$	0.407	0.029	-0.011	0.005	0.003	-.019	0.009	0.014	-0.006	-0.003	0.008	.912

5. FREQUENCY DOMAIN ANALYSIS OF VARIANCE

After the data are transformed to the frequency domain, a lagged model regression is performed on each component frequency. The results are shown in Table 4. The first row corresponds to the zero-frequency trend component. The column labelled density lists the spectral density distribution of the data. The trend component makes up 73.34 percent of the total spectrum. The total sum of squares (SST) of the variation about the mean of the data makes up 79.49 percent of that variation. The portion of SST that is error is represented by SSE and makes up 0.5494. The percentage that is explained by the MWS model R^2 is 99.3%. The sum of squares explained by the model is 79.49-0.5494= approximately 78.9430 (due to various computational rounding errors). The number of degrees of freedom for the univariate model is 1. So, the mean square explained by the model (MSM) is 78.9430/1=78.9430. The means square error = 0.5494/192 = 0.002876. MSM and MSE are chi square distributed so the ratio MSM/MSE =78.9430/0.002876 = approximately 27,444 is F distributed. Since the F = 27,444 test statistic is greater than 6.93, we conclude that the model is a good fit to the data. This is also true for each frequency component. In passing, we note that SSE is approximately constant across all frequencies suggesting that the data are stationary [Chatfield(1996, ch. 6)].

Table 4. Frequency domain Analysis of Variance

Freq	Period	Density%	SST%	SSE%	R^2	MSM	MSE	F
0	-	73.34	79.49	0.5494	0.993	78.9430	0.002876	27444
1	12	6.15	6.16	0.5281	0.914	5.6300	0.002765	2036
2	6	5.83	4.35	0.5052	0.884	3.8475	0.002645	1455
3	4	4.49	3.01	0.5159	0.829	2.4961	0.002701	924
4	3	3.17	1.70	0.5005	0.705	1.1966	0.002621	457
5	2.4	3.59	2.35	0.5131	0.782	1.8389	0.002686	685
6	2	3.44	2.94	0.5186	0.823	2.4172	0.002715	890
Grand total		100.00	100.00					

Table explanation:
FREQ-frequency. Number of cycles per window of length 12
PERIOD-time to complete one cycle
DENSITY-Relative size of this component
SST-total sum of squares
SSE-sum of squared errors
R^2-coefficient of determination
MSM-mean square explained by model (degrees of freedom = 1)
MSE-mean square unexplained by model (degrees of freedom =191)
F-(degrees of freedom in numerator = 1, denominator = 191, α=1%) = 6.93
Number of historical data points = 205.

6. TIME DOMAIN ANALYSIS OF VARIANCE

After all estimates are inverse transformed to the time domain, the analysis of variance is repeated. The results are shown in Table 5. The percentage of the variations in the data that are explained by the model R^2 is 38%. The Durban Watson static is expected to be biased so we use it sparingly. The value being less than the ideal of 2.0 suggests that there is some negative correlation in the data. The test statistic F = MSM/MSE ratio of 116.9 is greater than the theoretical value of 6.93. This suggests that the model is a good fit to the data and should have good predictive capability.

Table 5. Time domain Analysis of Variance

VARIABLE	SST	SSE	R^2	DW(192, 1)	MSM(1)	MSE(191)	F(1,191)
UASDE*	33588.50	20835.050	0.380	1.50	12753.45	109.084	116.9

* - units are in ('000')
SST - total sum of squares
SSE - sum of squared errors
R^2 - coefficient of determination
DW - Durbin Watson statistic (number of windows, number of variables)
MSM - mean square explained by model (degrees of freedom)
MSE - mean square unexplained by model (degrees of freedom)
F - (degrees of freedom in numerator, denominator, α = 1%) = 6.93
Number of historical data points = 205. Window length = 12

7. REVIEW OF THE MWS WINDOW LENGTH

Table 6 shows MSE(T) and R^2(T) for different values of window length. We recognize that in time series models the coefficient of determination (R^2) may be a biased measure of the actual fit (Maddala, 1992). So, in this analysis R^2 is used only as a measure of relative fit for each component of the model. Visual inspection of the data strongly suggested a periodicity of 12 months and therefore a window length of 12 months. As the window length departs from 12 months, MSE(t) rises sharply away from the optimal value of 109.084. A window length of 24 months will include two windows each of length 12 months. However, the number of windows is reduced. The result is MSE(T) =127.089, higher than the optimal value. There seems little chance of omitting any significant frequencies by limiting the window length to 12.

Table 6. MSE(t) and R^2 (T) for different window lengths

WINDOW LENGTH	**6**	**8**	**10**	**12**	**14**	**16**	**24**
MSE(T)	112.422	110.409	125.296	109.084	133.570	145.319	127.089
R^2 (T)	0.375	0.386	0.293	0.380	0.238	0.165	0.244

8. FORECAST

The forecast shown below (Table 7) shows the actual error, comparing forecast with real consumption data. The difference in the annual actual and forecast energy is 1.253%. This suggests that even when only an annual forecast is required it helps to make 12 monthly forecasts and add them. The mean absolute monthly forecast error is 9.254%. The table also shows the 50% prediction limits for the forecast, and in all cases, the actual consumption is between those limits. Figure 1 is the computer output from the forecasting software.

Table 7. Actual vs. Estimated Energy Consumption

	FORECAST KWH				
Date	**Lower prediction limit**	**Estimated**	**Upper prediction limit**	**Actual**	**%Error**
Apr-18	1276.733	1500.230	1723.727	1516.800	-1.092
May-18	1016.375	1332.648	1648.921	1521.600	-12.418
Jun-18	1112.409	1499.702	1886.995	1406.400	6.634
Jul-18	955.728	1403.024	1850.320	1348.800	4.020
Aug-18	959.888	1459.974	1960.060	1531.200	-4.652
Sep-18	800.074	1347.921	1895.768	1430.400	-5.766
Oct-18	802.437	1394.140	1985.844	1051.200	32.624
Nov-18	1027.386	1659.936	2292.486	1576.800	5.272
Dec-18	606.705	1277.760	1948.815	1670.400	-23.506
Jan-19	274.391	981.674	1688.956	936.000	4.880
Feb-19	411.971	1153.609	1895.247	1123.200	2.707
Mar-19	524.581	1299.107	2073.634	1404.000	-7.471
Annual	**9768.678**	**16309.73**	**22850.77**	**16516.8**	**1.253**
				Average Annual %Error	1.253
				Mean Absolute Monthly %Error	9.254

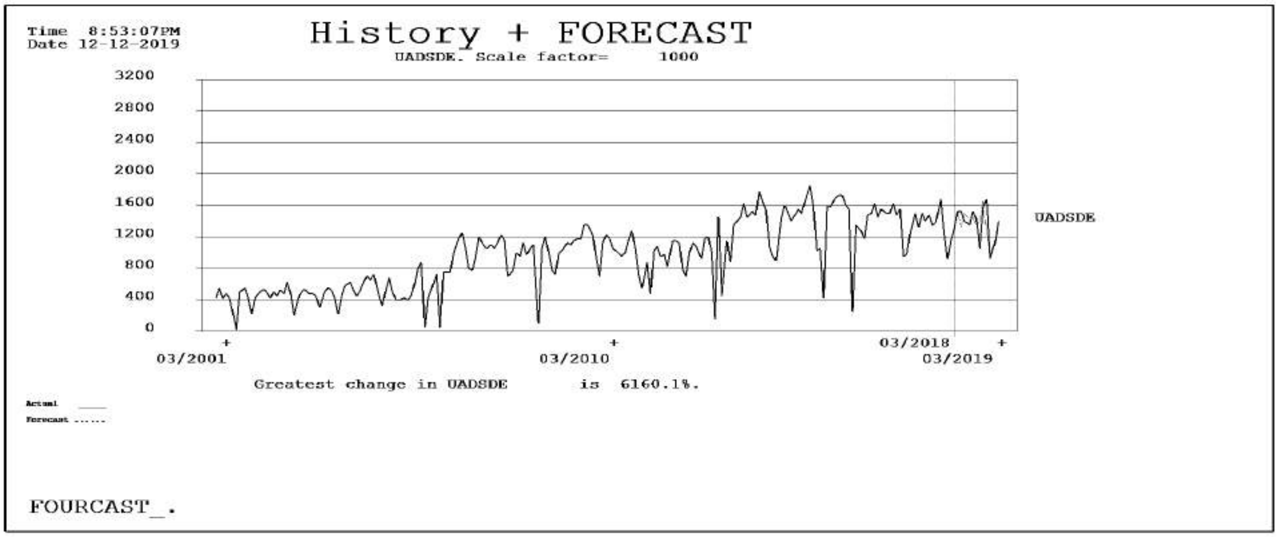

Figure 1. Forecast of Energy Consumption (in Kwh)

Figure 1 is a plot of the historical record of energy consumption for UASD for the period March 2001 to March 2019. It shows evidence of trend and seasonality. The forecasting model captures these components and uses them to develop the forecast for the 12-month period April 2018 to March 2019, as shown.

9. CONCLUDING REMARKS

The National Council of Energy of Dominican Republic requires that all public institutions control energy consumption and reduce waste. UASD is a public institution and must comply with that regulation. This includes maintaining a power factor of 0.90 to avoid penalties (SIE, 2007). Monitoring the energy use and controlling the power factor through a good forecast, we can better design the expansion and build new facilities.

Forecasting is essential for planning. In the short term, a forecast is needed to predict the needs for materials, products, services and other resources to respond to changes in demand. A Long-term energy forecast will allow us to make better selections of normal demand and emergency power plant equipment and systems.

The time series of monthly energy consumption for UASD was reviewed and found to be made up of trend, seasonal and multiple cyclical components. Therefore, it is imperative that model building and forecasting not be performed on the aggregate data for this time series. Instead, the data must first be decomposed into its components and each component forecast separately. That permits the components to evolve in different ways. We observed from inspection that the dominant cycle is twelve months. Therefore, the window length that was chosen to be appropriate was 12. Other possibilities are whole multiples of 12 equal to 24, 36,… Based on a 12 month window, a model was built for all but the last 12 months. The mean square error was found to be 109.084 kwh squared. To validate the choice of 12, the window length was varied from 6 to 24. The mean square error was lowest when the window length was 12.

Finally, the model was used to forecast the last 12 months and compare it with the last 12 actual months. The monthly forecast mean square absolute error is 9.254%. The annual forecast error is 1.253%. It is recommended that when an annual forecast is required, 12 monthly forecasts should be made and added. Because of the high accuracy, we conclude that the mws model and forecast are reliable methods for the university to use in analysis and planning for future electricity consumption and demand.

10. REFERENCES

[1] Azadeh, A., S.F. Ghaderi, S.F.,and Sohrabkhani, S. (2008). A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran. Energy Policy 36, 2637– 2644. https://doi.org/10.1016/j.enpol.2008.02.035

[2] Bianco, V., Manca, O., and Nardini S. (2013). Linear Regression Models to Forecast Electricity Consumption in Italy. Energy Sources, Part B, 8:86–93, https://doi.org/10.1080/15567240903289549.

[3] Chatfield, C. (1996). The Analysis of Time Series, 5th ed. Chapman and Hall, New York, NY.

[4] Cooley, J.W., & Tukey, J.W. (1965). An algorithm for the machine calculation of complex Fourier series. Math. of Comput., 19,297-301, and Special Issue (1967) IEEE Transactions on Audio and Electroacoustics.AU-15(2)45-117.

[5] Guo, H., Chen, Q, Xia, Q., Kang, C., and, Zhang, X. (2018). A monthly electricity consumption forecasting method based on vector error correction model and self-adaptive screening method. Electrical Power and Energy Systems 95 427–439. https://doi.org/10.1016/j.ijepes.2017.09.011

[6] Maddala, G. S. (1992). Introduction to Econometrics (2nd Edition), Prentice Hall, New Jersey.

[7] Ngnepieba, P., and Ridley, A. D. (2007). Univariate vs. Multivariate Moving Window Spectral Analysis, Refereed proceeding of the 11th World Multi-Conference on Systems, Cybernetics and Informatics, Vol. 4, Orlando, FL., USA, July 8-11.

[8] Panklib, K., Prakasvudhisarnb, C., and Khummongkol, D. (2015). Electricity Consumption Forecasting in Thailand Using an Artificial Neural Network and Multiple Linear Regression. Energy Sources, Part B, 10:427–434. DOI: 10.1080/15567249.2011.559520.

[9] Ridley, A. D. (2002). FOURCAST, Tallahassee, FL 32317-2518, USA. www.fourcast.net/fourcast.

[10] Ridley, A. D. (2001). Advances in model based dual chart process control. International Journal of Industrial Engineering, 8(1), 45-51.

[11] Ridley, A. D. (1994). A model-free power transformation to homoscedasticity. International Journal of Production Economics. 36, 191-202.

[12] Ridley, A. D. & Llaugel, F. (2000). Moving-window spectral neural-network model based feedforward process control. IEEE Transactions on Engineering Management, 47,393-402.

[13] Ridley, A.D. and Ngnepieba, P. (2009). The Multivariate Moving Window Spectral Method, Computers & Industrial Engineering, 56(1), pp11-18.

[14] Ridley, A.D. (2003).The Univariate Moving Window Spectral Method, Computers & Industrial Engineering, 45(4), pp. 691-711

[15] Ridley, A.D. and Womer, N.K. (1981). A Spectral Analysis of the Power Market in South Carolina, Refereed Proceedings Seventeenth Annual Meeting, S.E. Chap, The Institute of Management Sciences, October, Vol. XI, p. 12.

[16] Superintendencia de electricidad (SIE). (2007). Resolucion SIE-05-2007. Dominican Republic. January 8.