Prediction of electric energy consumption in small scale farming systems of Rwanda

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Abstract

The objective of this research was to forecast the electricity consumption in small scale farming systems of Rwanda using the easy and simple model, the case study of CAVM (College of Agriculture, Animal Sciences and Veterinary Medicine) - Rubilizi farm located in Kicukiro - Kigali, Rwanda. The classical time series decomposition forecasting model can help in the prediction of electric energy consumption which will simplify budget planning of the farm in terms of future electric energy use. The data analyzed were in a yearly format but subdivided in quarterly data; this was based on the quarterly report of the farm manager. The data analysis has been performed using classical decomposition time series method to forecast energy consumption for one year ahead. This paper clearly explains and presents classical decomposition times series methods in predicting energy consumption of Rubilizi Farm by using data set of 72 months (2009-2014).

The results showed that energy to be consumed in year 2015 were 832, 791, 691 and 881 kWh for quarter 1, quarter 2, quarter 3 and quarter 4 respectively. It has found errors of -0.0014, 0.0005, 6.3091% and 0.241549 respectively for bias, MAD, MAPE and MSE. Based on low values of the errors, it was concluded that the classical time series decomposition method can be used to forecast electric energy consumption in the small scale farm for the future period.

Key words: *Electricity consumption, prediction, classical decomposition, time series, small scale farm*

Introduction

Various techniques for forecasting electric energy consumption have been recommended in the last few years. For farmers, energy consumption forecast is useful in effectively planning the energy required in their future daily activities therefore responsible, efficient and well-planned power consumption is becoming a necessity (Samak, Morin, & Bailey, 2013)

Nowadays, Information technology is taking lead in various organizations to assist them in their jobs by storing the updated information and use that information to achieve the highest benefit by using several processing methods. Planning by predicting trends in the future is one way to apply statistical knowledge to analyze data in the past that are related to the current event. Then the results are used to predict future events (Chujai, Kerdprasop, & Kerdprasop, 2013).

Time series is the order of historical data, which resembles the group or observation of the data that have been collected over time according to the continuous period of time (Chujai et al., 2013). That collected data may already be in a daily, weekly, monthly, quarterly, or yearly format, depending on which one is appropriate to use (Chujai et al., 2013). Time series data consist of four components: trend, seasonal effect, cyclical, and irregular effect (Stevenson, 2010). The analysis of a time series used forecasting techniques to identify models from the past data. With the assumption that the information will be similar to itself in the future, we can therefore predict future events from the occurred data.

Time series decomposition can be used to separate or decompose a time series into seasonal, trend, and irregular components. While this method can be used for forecasting, its primary applicability is to get a better understanding of the time series. Many business and economic time series are maintained and published by government agencies such as the Census Bureau and the Bureau of Labor Statistics. These agencies use time series decomposition to create deseasonalized time series (Anderson, Sweeney, Williams, Camm, & Martin, 2011).

Understanding what is really going on with a time series often depends upon the use of deseasonalized data. For instance, we might be interested in learning whether electrical power consumption is increasing in our area. Suppose we learn that electric power consumption in September is down 3% from the previous month. Care must be exercised in using such information, because whenever

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a seasonal influence is present, such comparisons may be misleading if the data have not been deseasonalized. The fact that electric power consumption is down 3% from August to September might be only the seasonal effect associated with a decrease in the use of air conditioning and not because of a long-term decline in the use of electric power. Indeed, after adjusting the seasonal effect, we might even find that the use of electric power increased (Anderson et al., 2011).

There are several methods of statistical forecasting such as regressing analysis, classical decomposition method, Box and Jenkins and smoothing techniques. These techniques provide forecasting models of different accuracy. The accuracy of the prediction is based on the minimum error of the forecast. The suitable prediction methods are considered from several factors such as prediction interval, prediction period, characteristic of time series, and size of time series.

In the area of prediction, many researchers have used the method of forecasting with time series data such as the electric power consumption. (Popoola, 2015) applied this model to characterize the monthly output data of electricity generation from Ughelli Power Station, Nigeria, into its various components and replicate the original data in spite of the fluctuations, coupled with the noise, trend, cyclical activity and seasonal influences. In 1997, (Chen, 1997) tested the forecast performance of four major seasonal methods by using Monte Carlo simulation.

Within the purpose of energy consumption forecasting, (Bianco V. et al., 2009) applied gray prediction model. Forecasting consumption of conventional energy use in India, (Kumar U et al., 2009) executed Grey-Markov model, Grey-Model with rolling mechanism, and singular spectrum analysis models. Having the purpose of predicting the electricity consumption in Perlis (Syariza and Norhafiza, 2005) compared various forecasting methods. However, it is known that Box-Jenkins method is one of the most popular forecasting methods, in their study, they found that the Box-Jenkins method is not appropriate to use, also they indicated that regression model is much better for their problem. Afterwards another study came into light, the studies by (Taylor ,2008) showed that exponential smoothing method is more reliable and appropriate for short term prediction.

In this research, we are interested in classical decomposition time series analysis because

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the time series decomposition models do not involve a lot of mathematics or statistics; they are relatively easy to explain to the end user, therefore cheaper as compared with other models. This is a major advantage because if the end user has an appreciation of how the forecast was developed, he or she may have more confidence in its use for decision making.

Many researchers had put lot of efforts in developing tools and models for forecasting. Analyzing the historical data and apply statistical knowledge in order to relate the predicted values with data in the past and also reflect the characteristics of time series are very crucial. Time series comprised of the data that have been collected over time with the continuous period of time. In this paper, the data analyzed were in a yearly format but subdivided in quarterly data; this is based on the quarterly report of the farm manager. For the energy efficient concerns, we will provide next one year electricity consumption forecasts in order to reveal the potential consumption, cost and savings. Prediction of the electricity consumption of CAVM-Rubilizi farm is important for taking energy efficient and planning decisions.

Methodology

The classical time series decomposition method was used to forecast energy composition in CAVM-Rubilizi farm. The data collected and analyzed were from the year 2009 to 2014

As our data (presented in table 1) reflected time series data which were seasonally increasing, multiplicative decomposition were used during this study.

Therefore,

$$Y_t = S_t \times I_t \times T_t \qquad (1)$$

Where

Y_t: is original data at time period t (which is *Electricity consumption* in our context)

S_t: is seasonal value at time period t

I_t: is irregular value at time period t

T_t: is trend value at time period t

We assumed that any irregular component that was present would be captured by the trend, and therefore would not deal with it separately.

That simplifies our model to

$$Y_t = S_t \times T_t \qquad (2)$$

The steps followed in applying the decomposition method are as follows:

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(1) First a moving average of length n is computed for the time series. The value of n is taken as equal to the length of seasonality. For instance, we have quarterly data, n= 4. This step reduces random variations and eliminates seasonality. Then we centre this moving average and obtain the centered moving average.

(2) Next, the actual value of the time series for each period is compared with its centered moving average (obtained in step 1).

The resulting ratio is the seasonality factor estimate:

$$s_t = \frac{Y_t}{Centered\ moving\ average\ at\ time\ t} \qquad (3)$$

(3) For more than one year's data, the seasonality factor is averaged for each of the periods of the seasonal cycle. The factors should total up to the number of periods n per cycle. If they do not, then they should be adjusted so that they add up to n.

(4) Next, the time series should be deseasonalized. The formula used here is:

$$T_t = \frac{Y_t}{S_t} \qquad (4)$$

5) Next, the trend is estimated for the deseasonalized data using simple linear regression analysis or by moving averages with trend adjustments. In case a linear trend results, then the resulting values are **a** (intercept) and **b** (slope).

(6) The forecast for period t + m can now be prepared using the relation

$$Y_{t+m} = [a + b(t+m)]S_{t+m} \qquad (5)$$

Measuring forecast accuracy

Bias error

It is simply an arithmetic mean of errors; we would like it to become zero. A positive one means that the model on the average forecasts low whereas the negative one means the reverse.

$$Bias = \frac{\sum(Actual - Forecast)}{n} \qquad (6)$$

Mean Absolute Deviation (MAD)

MAD penalizes all errors equally, in direct proportion to their magnitude.

The MAD means the amount by which the forecast model missed on the average.

$$MAD = \frac{\sum ABS(Actual - Forecast)}{n} \qquad (7)$$

Mean Absolute Percent Error (MAPE)

This is like MAD, but penalizes error on the basis of what proportion of the actual value it is rather than its raw numeric amount.

$$MAPE = \frac{\sum \frac{ABS(Actual - Forecast)}{Actual}}{n} \qquad (8)$$

Mean Squared Error (MSE)

It is very much like the simple variance. It penalizes larger errors much more heavily than smaller ones

$$MSE = \frac{\sum(Actual - Forecast)^2}{n} \qquad (9)$$

Results and Discussion

Figures 1 – 3 and Table 1 show the results obtained from CAVM-Rubilizi Farm electric energy consumption data decomposition analysis. The trend displays a linear increasing trend as shown in figure 1.

Results also elucidated that there are seasonal effects in electric energy consumption as shown in figures 2 and 4. We also have the four seasonal indices and we have estimated that:

- The electric energy consumption for the January -March quarter is 107 % of the average quarter.
- The electric energy consumption for the April-June quarter is 100 % of the average quarter.
- The electric energy consumption for the July-September quarter is 85 % of the average quarter.
- The electric energy consumption for the October-December quarter is 107 % of the average quarter.

It was found that the classical time series decomposition method can be used to forecast electric energy consumption for the future period (year 2015) as presented and highlighted in table 1.

After decomposition of all components from the main data as shown in figure 1, 2 and 3, we combined all of them to forecast the electric energy consumption of CAVM-Rubilizi Farm and the results are presented in figure 4 and table 1.

This study is limited to single farm, CAVM-Rubilizi Farm, located at Kicukiro, Kigali-Rwanda. The electric energy consumption data employed were those made available by the farm Manager.

Table 1: Decomposition analysis of electric energy consumption data for CAVM-Rubilizi Farm

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Period (t)	Year	Quarter	Electricity consumption[100kWh]	Moving Average (4)	Centered moving average(4)	S_t, I_t	Seasonal Indices (S_t)	Deseasonalized data (D_t)	Trend (T_t)	Prediction[100kWh]
1	Year 2009	1	3.94				1.07	3.67	3.66	3.93
2		2	4.34				1.00	4.34	3.83	3.83
3		3	3.59	4.24	4.33	0.83	0.85	4.20	4.00	3.42
4		4	5.10	4.42	4.42	1.15	1.07	4.78	4.17	4.45
5	Year 2010	1	4.66	4.43	4.47	1.04	1.07	4.34	4.34	4.66
6		2	4.36	4.52	4.53	0.96	1.00	4.36	4.51	4.51
7		3	3.96	4.54	4.62	0.86	0.85	4.63	4.68	4.00
8		4	5.18	4.71	4.76	1.09	1.07	4.85	4.85	5.18
9	Year 2011	1	5.33	4.82	4.86	1.10	1.07	4.96	5.02	5.39
10		2	4.82	4.91	4.94	0.98	1.00	4.82	5.19	5.19
11		3	4.30	4.98	4.97	0.87	0.85	5.03	5.36	4.58
12		4	5.46	4.95	4.98	1.10	1.07	5.12	5.53	5.90
13	Year 2012	1	5.23	5.01	5.08	1.03	1.07	4.87	5.70	6.12
14		2	5.04	5.15	5.21	0.97	1.00	5.04	5.87	5.87
15		3	4.88	5.27	5.56	0.88	0.85	5.71	6.04	5.16
16		4	5.92	5.85	6.20	0.95	1.07	5.55	6.21	6.63
17	Year 2013	1	7.57	6.56	6.72	1.13	1.07	7.05	6.38	6.86
18		2	7.86	6.89	7.10	1.11	1.00	7.86	6.55	6.55
19		3	6.20	7.31	7.34	0.84	0.85	7.25	6.72	5.75
20		4	7.62	7.36	7.27	1.05	1.07	7.14	6.89	7.36
21	Year 2014	1	7.77	7.19	7.20	1.08	1.07	7.23	7.06	7.59
22		2	7.15	7.22	7.26	0.99	1.00	7.15	7.23	7.23
23		3	6.33	7.29			0.85	7.41	7.40	6.33
24		4	7.92				1.07	7.42	7.57	8.08

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25	Year 2015	1					1.07		7.74	**8.32**
26		2					1.00		7.91	**7.91**
27		3					0.85		8.08	**6.91**
28		4					1.07		8.25	**8.81**

One year ahead forecasting

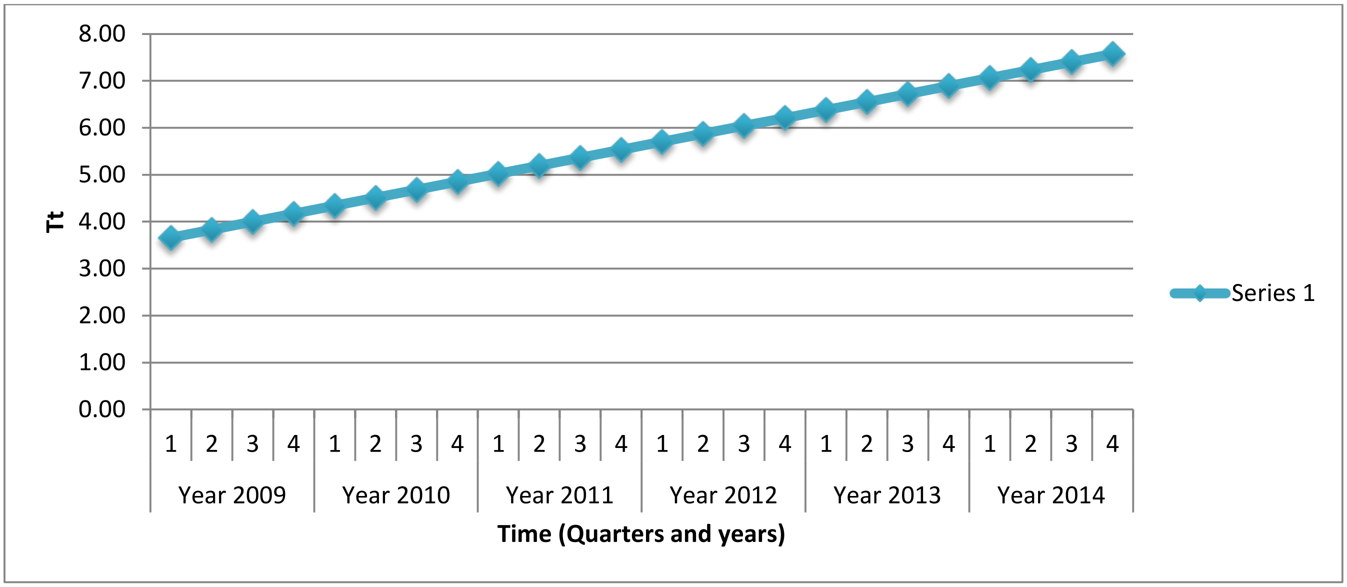

Figure 1: Trend versus time

Table 2: Errors evaluation

	Bias	**MAD**	**MAPE (%)**	**MSE**
Errors value	**-0.0014**	**0.0005**	**6.3091**	**0.241549**
Discussions	Model average forecasts almost the same as the actual value	The amount by which the forecast model missed on the average is very small which means that the model chosen for prediction is performing well	This means that the accuracy of the model chosen is about 94 %.	As MSE is very low, it means that the variance of forecast error is also too small therefore the model used for prediction is adequate to this type of data

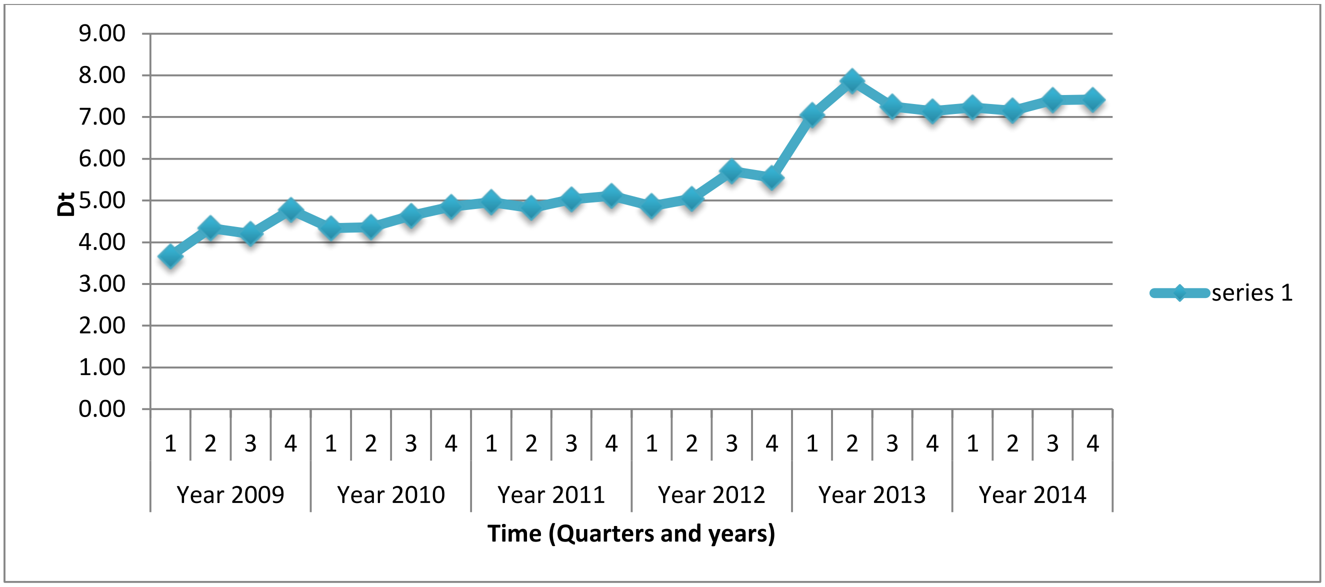

Figure 2: Deseasonalized data versus time

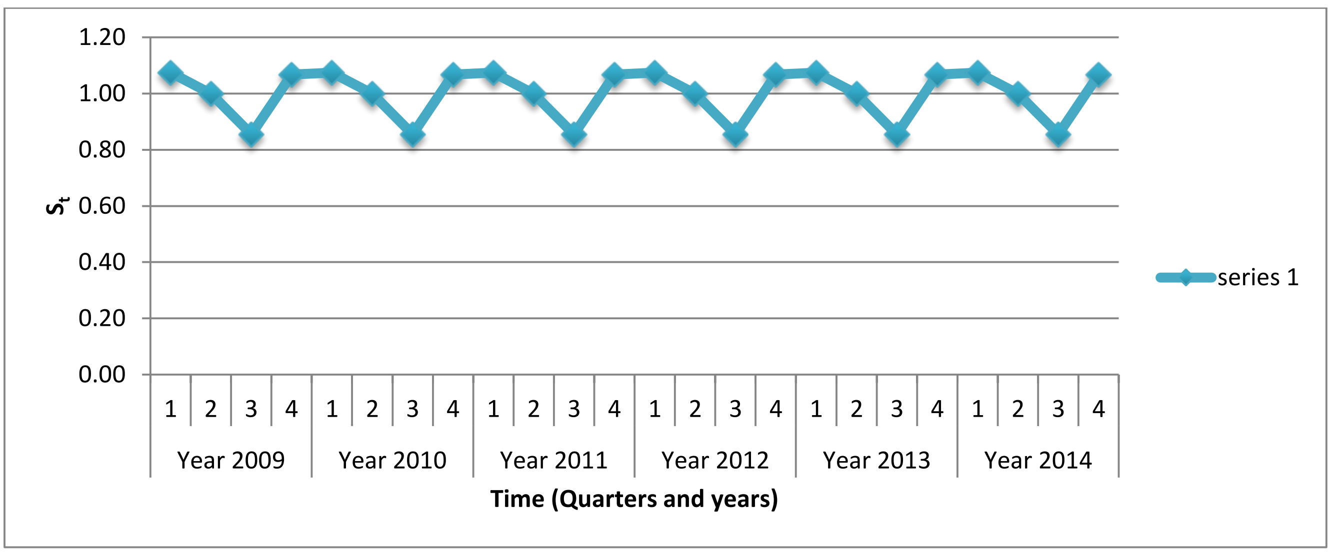

Figure 3: Seasonal index versus time

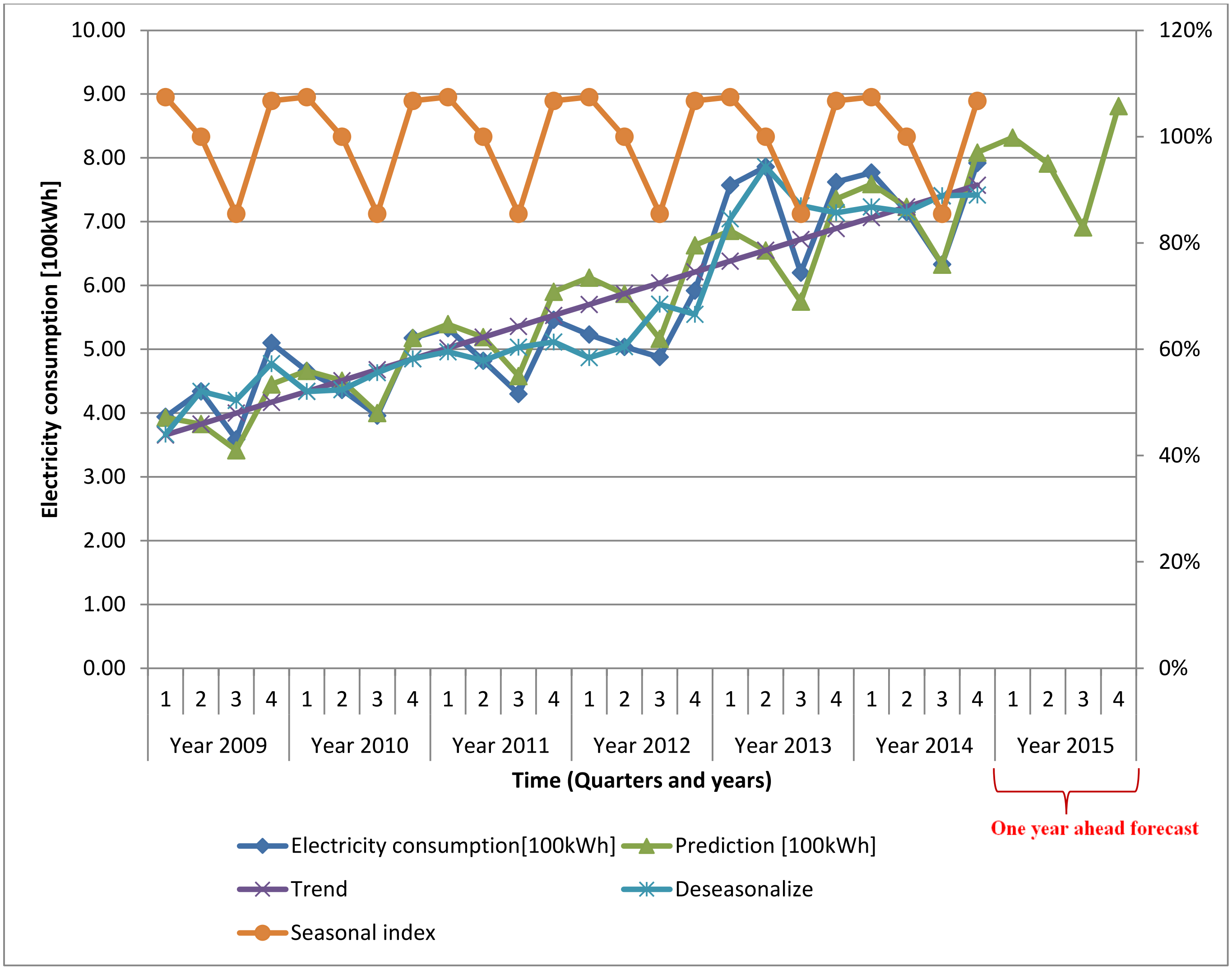

Figure 4: Prediction of Rubilizi farm Electric Energy Consumption (Deseasonalized, trend and seasonal effects)

Results and discussions about errors evaluation

The model presented errors of -0.0014, 0.0005, 6.3091% and 0.241549 respectively for bias, MAD, MAPE and MSE, for the type of data which were being analyzed, we have realized that the predicted data versus the original data are presenting a very small error which make the classical time series decomposition method to be one of the best fitting forecasting models. Errors evaluation are presented in table 2

Conclusion

It is known that in developing countries like Rwanda, small scale farmers often do not have sufficient resources enjoyed by larger farmers, under such conditions, predicting electric energy consumption may be done more by instinct or by guesswork than by the proper data analysis and forecast methodology. This paper shows that there are other alternatives to overcome those problems.

We have been able to develop the model that track and describe the original electricity consumption data from UR/CAVM Rubilizi farm, located at Kicukiro. The model employed was able to characterize the quarterly output data into its various components and replicate the original data in spite of the fluctuations, coupled with the noise, trend, cyclical activity and seasonal influences. This is evident from the results obtained in the final decomposition shown above in column 11 as compared to the electricity consumption data in column 4 of table 1. The classical decomposition model forecasted also for one year ahead and the results showed the electricity consumption of 832, 791, 691 and 881 kWh respectively for quarter 1, quarter 2, quarter 3 and quarter 4 for the year 2015. The errors evaluation showed that the classical time series decomposition is well suited for CAVM Rubilizi farm electricity consumption data in matter of forecasting as the errors obtained are small.

Farms which present the same degree of regularities to electric energy consumption data may utilize the method described here in to study and decompose the components of electric energy consumption data. Once these components are obtained, forecasting electric energy consumption can easily be made for future periods by recombining these components.

Acknowledgments

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