Forecasting Rainfall Distribution Based on Deseasonalising Fuzzy Time Series Model

Siti Nor Fathihah Azahari, Mahmod Othman
Faculty of Computer Science and Mathematic
University of MARA Technology Arau, 02600 Perlis, Malaysia.
mahmod135085@perlis.uitm.edu.my

***Abstract*—Rainfall prediction is an essential process to reduce loss of lives and properties. However, the accuracy of this prediction has been of many concerns in literature. Therefore, this paper proposed a model of rainfall prediction based on deseasonalising data and fuzzy time series concept. The historical data of rainfall distribution were collected from Drainage and Irrigation Department, Perlis Malaysia between January 2000 and December 2013. These data were analysed in order to determine the seasonal components using fuzzy time series as a medium. The study made use of deseasonalising rainfall data by employing fuzzy time series model in order to forecast the rainfall distribution. The model performance was evaluated by using statistical criteria of Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The obtained result was compared with several forecasting models in literature and it was found to be more accurate than others. Hence, this study demonstrates that fuzzy time series model is more suitable for the accurate prediction of rainfall distributions.**

***Index Terms*—Rainfall Distribution; Fuzzy Time Series; Forecasting; Deseasonalising.**

I. INTRODUCTION

Every year, there is increase in the number of loss of life and damaged properties worldwide due to heavy rainfalls and floods [1]. This has led to many prediction studies such as studies [2,3,4,5,6,7]. For instance, in study [4], the researchers presented a model of rainfall prediction based on polynomial regression while data were collected in Myanmar. Similarly study [5] proposed another prediction model based on nonlinear statistical ensemble using Particle Swarm Optimization (PSO) algorithm in order to predict short-range rainfall in Guangxi China. The study implemented neuro-fuzzy networks with the assimilation of multi-sensor information in order to achieve its objective of watershed rainfall forecast. In addition, study [2] presented a non-linear model of rainfall-runoff based on first-order Takagi–Sugeno fuzzy system. Likewise, study [7] was carried out in Bangkok Thailand where a rainfall forecasting model based on an artificial neural network was proposed.

Although, these studies have explicitly depicted that it is possible to predict rainfall distribution. However, there is still concern about the accurate prediction of these studies [3,5]. In the same manner, it can be seen in the literature that there is limited application of fuzzy time series theory to forecast rainfall distribution. Meanwhile, due to the probability nature of rainfall distribution, study [8] argued that fuzzy time series will be the most suitable for predictions. Although study [8] employed fuzzy time series for rainfall predictions, however the study only implemented first-order time variant of fuzzy series model. The study was carried out on prediction of runoff rainfalls in the region of Ambikapur Chhattisgarh.

Furthermore, it can be seen in literature that fuzzy time series theory have been used in various prediction studies such as studies [9-13]. Specifically studies [10,12] shows that fuzzy time series theory has been adopted to forecast the enrolment of student in universities and tourism demand. Similarly, studies [14-17] have reflected the application of fuzzy time series model in accurate prediction of phenomena in the entire literature. Thus, this present study implemented fuzzy time series theory in order to accurately predict rainfall distributions [8,9,15].

We briefly review the basic concept of fuzzy time series that were introduced in this study. If U is the universe of discourse, $U = \{u_1, u_2, ..., u_n\}$, and if X is a fuzzy set in the universe of discourse U defined as follows:

$$X = f_X(u_1)/u_1 + f_X(u_2)/u_2 + \cdots + f_X(u_n)/u_n \tag{1}$$

where f_X is the membership function of X, $f_X : U \rightarrow [0,1]$, $f_X\ (u_1)$ means the grade of membership of u_i in the fuzzy set X, $f_X(u_i) \in [0,1]$, and $1 \le i \le n$, the symbol "/ " split the elements from the grades of membership in the universe of discourse U. Meanwhile "+ " indicates "union".

If $W_a(t)$ $(t = ..., 0,1,2, ...)$ is the universe of discourse and is the subset of R_a, let fuzzy set $x_i(t)$ $(i = 1,2, ...)$ be described in $W_a\ (t)$. Let $X_a(t)$ be a collection of x_i(t) $(i = 1,2, ...)$. Then, $X_a(t)$ is called a fuzzy time series of $W_a\ (t)$ $(t = ..., 0, 1, 2, ...)$.

Then X_a is caused by $X_a(t\text{-}1)$, indicated by $X_a(t\text{-}1) \rightarrow X_a$, where this relationship can be represented by $X_a = X_a(t\text{-}1) \circ R_a(t, t\text{-}1)$, where the symbol " ∘ " is a composition operator symbol of the Max-Min; $R_a(t, t\text{-}1)$ is a fuzzy relation between $X_a(t)$ and $X_a(t\text{-}1)$ and is known as the first-order model of $X_a(t)$.

Whereas, $X_a(t)$ be a fuzzy time series and also $R_a(t, t\text{-}1)$ be a first-order model of $X_a(t)$. If $R_a(t, t\text{-}1) = R_a(t\text{-}1, t\text{-}2)$ for any time t, then $X_a(t)$ is known as a time-variant fuzzy time series. If $R_a(t, t\text{-}1)$ is dependent on time t, in addition $X_a(t)$ is known as a time-variant fuzzy time series. Then, the stepwise procedures follows define the fuzzy time series of Song and Chissom model.

Step 1: The universe of discourse U is defined from the historical data. The smallest data value is assumed as *Dmin* and the largest data value is assumed as *Dmax*. Hence, the Universe $U = [Dmin, Dmax]$. Make sure that the *Dmin* and *Dmax* are in the whole number.

Step 2: The universe of discourse U is divided into equal length of interval; $u_1, u_2, \ldots, u_n$. Assign each of the interval with fuzzy set $A_1, A_2, \ldots, A_n$.

Step 3: Each of the fuzzy set A_i from step 2 is defined where if the fuzzy set are $A_1, A_2, \ldots, A_n$, then the fuzzy set A_i, $\forall i = 1,2,\ldots,n$ can be described as $Ai = f_{A_i}(u_1)/u_1 + f_{A_i}(u_2)/u_2 + \cdots + f_{A_i}(u_n)/u_n$.

Step 4: The historical data is fuzzify.

Step 5: A suitable parameter v, where $v > 1$, $R^v(t, t-1)$ and predict the data as follow:

$$Xa(t) = Xa(t-1)^{\circ}R^v(t, t-1), \quad (2)$$

where $Xa(t)$ indicates the forecast fuzzy data of year t, $Xa(t-1)$ indicates the fuzzified data of year t-1, and

$$R^v(t, t-1), = Xa(t-2) \times X(t-1) \cup X(t-3) \times X(t-2) \cup \ldots \cup Xa(t-w) \times X(t-w+1), \quad (3)$$

where w is denoted as 'model basis' denoting the number of years before t, $F(t)$ is the forecasting fuzzy of year t, "$\times$"is the symbol of Cartesian product operator, and T is the transpose operator.

Step 6: The forecasted output is determined. If the time series data $A(t)$, $\forall i = 1,2,\ldots,m$, then the forecast of $Fa(k+1)$ is obtained as $Fa(k+1) = Ai^{\circ}R, \forall t \in [1,n],\ i = 1,2,\ldots,m$.

Step 7: The forecast output is interpreted. Each of the forecasting value is defuzzified based on the centroid method.

II. METHODOLOGY

A. Data Collection

The procedure followed for this study data collection can be summarized in Figure 1.

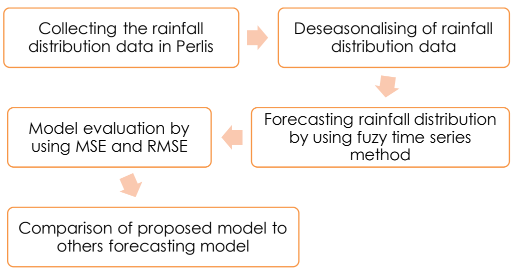

Figure 1: Block diagram of rainfall distribution forecasting based on fuzzy time series concept

Figure 1 shows the block diagram of rainfall distribution forecasting based on fuzzy time series concept. It started from the stage of data collection of rainfall distribution in Perlis Malaysia. Then, the historical data were deseasonalised. The deseasonalising rainfall data implied the forecast of rainfall distribution by using the fuzzy time series concept. Next, the model evaluation was done using three different models to compare. Model 1 was the proposed forecasting rainfall of fuzzy time series based on deseasonalising rainfall data, Model 2 was the forecasting rainfall of fuzzy time series based on actual rainfall data which have seasonal component while Model 3 was the Danni and Sharma Model. For the comparison Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) were implemented in order to identify the most accurate model.

B. *An application of fuzzy time series concepts to forecast the rainfall distribution.*

In this section, the fuzzy time series concept was applied to rainfall distribution prediction in Perlis. The rainfall distribution data in Perlis were collected from Perlis's Department of Drainage and Irrigation (DID) from January 2000 until December 2013. Instead of meteorology department, the drainage and irrigation department Malaysia is assigned the responsibility of accounting for rainfall statistics in Malaysia. Table 1 summarized the deseasonalising rainfall statistics.

Table 1
Deseasonalising rainfall distribution data

Month	Actual Rainfall Data (mm)	Deseasonalising Rainfall Data (mm)	Sub Interval
2000/01	71.47	71.17	S4
2000/02	87.43	87.07	S5
2000/03	189.97	188.94	S12
2000/04	241.27	240.18	S16
2000/05	209.10	208.24	S13
2000/06	204.47	203.56	S13
2000/07	127.27	126.25	S7
2000/08	234.98	233.87	S15
2000/09	247.23	245.78	S16
2000/10	239.40	237.81	S15
2000/11	266.83	265.47	S16
2000/12	69.67	68.76	S4
2001/01	170.53	170.23	S11
2001/02	24.15	23.79	S2
2001/03	175.60	174.57	S11
2001/04	201.10	200.01	S13
2001/05	121.30	120.44	S7
2001/06	145.80	144.89	S9
2001/07	79.90	78.88	S4
2001/08	239.40	238.29	S15
2001/09	143.81	142.36	S8
2001/10	323.43	321.84	S18
2001/11	172.45	171.09	S11
2001/12	126.07	125.16	S7

From the table, seasonal components which are also known as seasonal variation were analysed. The analysis reflected that there were regular fluctuation periods within the regulatory pattern as specified by the time intervals. For instance, the fluctuation are more pronounced when the analysed data were viewed within months and years [16]. In order to ensure accuracy of the model, the seasonal component were removed which is known as deseasonalisation [17,18]. Computed analysis on the seasonal components was presented in the second column on the table. Further details on the data analysis are hereby presented in seven different steps tagged as Steps 1-7.

Step 1: The universe of discourse U from historical data was defined; U = [0,480].

Step 2: The universe of discourse U was divided into eight intervals of linguistic value based on the Table 2 in first column.

Step 3: The universe U from step 2 was re-divided to obtain sub-interval by identifying the frequency of rainfall data for every months, in each interval of linguistic value u_1 till u_8. Then, the frequency of interval was ranked from the highest to the lowest number of frequency. Table 3, shows the partition of equal length interval to sub-interval, Sj, from S1 to S20.

Step 4: Each of the rainfall data were identified for their sub-interval. The result of the determination of the sub-interval was depicted on Table 1 in forth column, Sub-Interval

Step 5: The rule of rainfall forecasting was determined based on the three types of rules and Table 4;

Rule 1: This rule was valid only for the beginning of data, which were February and March 2000. The previous two (2) month of data were needed. The prediction in February 2000 was involved only in January 2000. Hence, if the *(│(the subtraction of January 2000 and Zero (0) data)│ × 2 +* R_t*)* is in the sub-interval S_j, then the rainfall forecasting go upward at the ¾ point of this interval; if *(│(the subtraction of January 2000 and Zero (0) data)│/ 2+* R_t*)* is in the sub-interval S_j, then the rainfall forecasting go downward at the ¼ point of this sub-interval; if it is not the case, the rainfall forecast be the ½ point value of the corresponding sub-interval S_j. Meanwhile, to forecast rainfall in March 2000, if *(│(the subtraction of February 2000 and January 2000)│ × 2 +* R_t*)* is in the sub-interval S_j, then the rainfall forecasting go upward at the ¾ point of this interval; if *(│(the subtraction of February 2000 and January 2000)│ / 2 +* R_t*)* is in the sub-interval S_j, then the rainfall forecasting go downward at the ¼ point of this sub-interval; if it is not the case, the rainfall forecast be the ½ point value of the corresponding sub-interval S_j.

Rule 2: If $(\left|(V_{t-1} - V_{t-2}) - (V_{t-2} - V_{t-3})\right| \times 2 + R_t)$ falls in the corresponding interval S_j, then the rainfall forecasting go upward at the ¾ point of this interval; If $(\left|(V_{t-1} - V_{t-2}) - (V_{t-2} - V_{t-3})\right| / 2 + + R_t)$ falls in the corresponding interval S_j, then the rainfall forecasting go downward at the ¼ point of this interval; if it is not the case, the rainfall forecast be the ½ point value of the corresponding interval S_j.

Rule 3: If $(\left|(V_{t-1} - V_{t-2}) - (V_{t-2} - V_{t-3})\right| / 2 + R_t)$ falls in the corresponding interval S_j, then the rainfall forecasting go downward at the ¼ point of this interval; If $(\left|(V_{t-1} - V_{t-2}) - (V_{t-2} - V_{t-3})\right| \times 2 + R_t)$ falls in the corresponding interval S_j, then the rainfall forecasting go upward at the ¾ point of this interval; if it is not the case, the rainfall forecast be the ½ point value of the corresponding interval S_j,

Based on Table 4, V_t was current rainfall prediction (*mm*); V_{t-1} is rainfall for a month before (*mm*); V_{t-2} is rainfall for two month before (*mm*); and V_{t-3} rainfall for three month before (*mm*). There were three types of rules to determine the trend of forecasting as described in Table 4. Each of the rules had their terms and conditions. Table 4 shows how categorization was done using the rule of rainfall forecasting for each current prediction data. Based on Table 4, Equation (4) and (5) were used to apply starting from data April 2000 to December 2013. This was because the prediction of current rainfall data was involved in subtraction of 3 month of the previous data.

For example, the rule of the month of May 2000 was calculated (the difference of rainfall data in April 2000 and March 2000) which were subtracted (the difference of rainfall data in Mac 2000 and February 2000). Then, the obtained result was positive values. Thus, the data for May 2000 were categorised as Rule 3. Meanwhile, the first month of January 2000 that was also the beginning of rainfall data collected were not been forecasted because there were no previous rainfall data. Consideration was made from February and March 2000 for special case in forecasting parts of this consideration which were insufficient of three months of previous data. So, there are considering in Rule 1.

Step 6: The trend of each rainfall data were identified based on the rules of forecasting in Step 5, whether it is in the downward, upward or middle trend. Table 5 shows the result of trend (third column) based on the rule of forecasting which further depicts the prediction of rainfall as deduced from the proposed model.

Moreover, the result of rainfall distribution prediction was presented in Table 5 fourth column. The forecasting result were determined based on the trend gotten from the third column by employing rule of forecasting as stated in Step 5. The trends were found to be between middle, upward or downward.

Step 7: The result of forecasting was evaluated by using two types of statistical criterion; Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The criterion to differentiate between a poor forecast model and good forecast model is call "error measure" [16,19]. Furthermore, MSE and RMSE were adopted as error measurement in order to obtain a more precise fuzzy time series model which can be more accurate than other previous prediction model in literature. Analysis used for MSE and RMSE were presented in Equation 6 and 7.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{(Actual\ rainfall_i - Forecasted\ Rainfall_i)^2}{Actual\ rainfall_i} \right| \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left|(Actual\ Rainfall_i - Forecasted\ Rainfall_i)^2\right|}{n}} \quad (7)$$

Table 2
The equal length interval

Equal length intervals	Frequency	Rank	Re-divide
u1=[0, 60]	23	3	3
u2=[60, 120]	23	3	3
u3=[120, 180]	52	1	5
u4=[180, 240]	37	2	2
u5=[240, 300]	19	4	4
u6=[300, 360]	7	5	-
u7=[360, 420]	2	7	-
u8=[420, 480]	5	6	-

Table 3
The sub-interval, *Si*

Sj	Range	*Si*	Range
S1	u1,1 = [0, 20]	S2	u1,2 = [20, 40]
S3	u1,3 = [40, 60]	S4	u2,1 = [60, 80]
S5	u2,2 = [80,100]	S6	u2,3=[100, 120]
S7	u3,1 = [120, 132]	S8	u3,2=[132, 144]
S9	u3,3 = [144, 156]	S10	u3,4=[156, 168]
S11	u3,5= [168, 180]	S12	u4,1=[180, 195]
S13	u4,2= [195, 210]	S14	u4,3=[210, 225]
S15	u4,4= [225, 240]	S16	u5 = [240, 270]
S17	u6 = [270, 300]	S18	u7 = [300, 360]
S19	u8 = [360, 420]	S20	u9 = [420, 480]

Table 4
The categorizing the rule of forecasting

Calculation of rainfall data	Rule of Forecasting
$V_{t\text{-}1}\text{-}V_{t\text{-}2}$	Rule 1
$(V_{t\text{-}1}\text{-}V_{t\text{-}2})\text{-}(V_{t\text{-}2}\text{-}V_{t\text{-}3}) = +\text{ve}$ (4)	Rule 2
$(V_{t\text{-}1}\text{-}V_{t\text{-}2})\text{-}(V_{t\text{-}2}\text{-}V_{t\text{-}3}) = -\text{ve}$ (5)	Rule 3

Table 5
The trend of rule of forecasting

Month	Deseasonalising Rainfall Data	Trend	Forecast value
2000/01	71.17	-	-
2000/02	87.07	Middle	90
2000/03	188.94	Middle	187.5
2000/04	240.18	Middle	255
2000/05	208.24	Middle	202.5
2000/06	203.56	Middle	202.5
2000/07	126.25	Middle	126
2000/08	233.87	Middle	232.5
2000/09	245.78	Middle	255
2000/10	237.81	Middle	232.5
2000/11	265.47	Middle	255
2000/12	68.76	Middle	70
2001/01	170.23	Middle	174
2001/02	23.79	Middle	30
2001/03	174.57	Middle	174
2001/04	200.01	Middle	202.5
2001/05	120.44	Middle	126
2001/06	144.89	Middle	150
2001/07	78.88	Middle	70
2001/08	238.29	Middle	232.5
2001/09	142.36	Middle	138
2001/10	321.84	Middle	330
2001/11	171.09	Middle	174
2001/12	125.16	Middle	126

Note: Middle is stand for ½ point value of trend

III. RESULT AND DISCUSSION

The result of this study analysis reflected three forecasting models as summarized in Table 6. Model 1 was developed based on deseasonalising rainfall data while Model 2 was based on actual rainfall data. These two models made used of fuzzy time series of rainfall forecasting while the third model was based on Dani and Sharma Model.

The results obtained from MSE and RMSE on these models can be inferred from Table 6. It can be seen that Model 1 gave 47.24 and 6.87 of MSE and RMSE respectively. Meanwhile, in Model 2 higher values were obtained which were 76.47 and 8.74 for MSE and RMSE respectively. Similarly, trend was observed in model 3 were the values 128.81 and 11.35 obtained for MSE and RMSE respectively. This implies that Model 1 using deseasonalising rainfall data has the smallest error measurement compared with other two models.

Hence, the proposed model shows highest accuracy of rainfall prediction with less error of forecasting. Therefore, this study concludes that the proposed fuzzy time series model based on deseasonalising rainfall data (presented as Model 1 in Table 6) is found to be more reliable and accurate.

Table 6
The result of rainfall forecasting

Deseasonalising Rainfall Data	Model 1	Model 2	Model 3
71.17	-	-	-
87.07	90	90	90
188.94	187.5	187.5	187.5
240.18	255	255	255
208.24	202.5	202.5	195
203.56	202.5	202.5	195
126.25	126	126	127.5
233.87	232.5	232.5	225
245.78	255	255	270
237.81	232.5	232.5	225
265.47	255	255	255
68.76	70	70	70
170.23	174	174	172.5
23.79	30	30	30
174.57	174	174	172.5
200.01	202.5	202.5	195
120.44	126	126	127.5
144.89	150	150	142.5
78.88	70	70	70
238.29	232.5	232.5	225
142.36	138	138	142.5
321.84	330	330	330
171.09	174	174	172.5
125.16	126	126	127.5
MSE	47.24	76.47	128.81
RMSE	6.87	8.74	11.35

Note: Model 1 is proposed forecasting rainfall of fuzzy time series using deseasonalising rainfall data; Model 2 is proposed forecasting rainfall of fuzzy time series using actual rainfall data that have seasonal component; Model 3 is Danni and Sharma Model

IV. CONCLUSION

This study has been able to present rainfall prediction model based on fuzzy time series. The model was compared with two other models in the literature. One of the compared models was based on actual data of rainfall distribution based on seasonal component. The data shows the seasonal component and the process of removing these seasonal components which is deseasonalising. The result obtained depicts that the proposed model of fuzzy time series of rainfall forecasting based on deseasonalising rainfall data has the smallest MSE and RMSE compared to other two models compared. The lowest error measure of the proposed model made it to be more accurate and reliable than the other two.

ACKNOWLEDGEMENT

The study was funded by “Long Term Research Grant (LRGS) (UUM/RIMPC/P-30)”. A lot of thanks to Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA for providing the laboratory facilities for completing the study. Last but not least, Perlis’s Drianage and Irrigation Department (DID) that had provide the Perlis’s rainfall distribution data for this research.

REFERENCES

[1] Asklany S. A., Elhelow K., Youssef I. K., and Abd El-wahab M. 2011.Rainfall Events Prediction Using Rule-Based Fuzzy Inference System. *Atmospheric Researchl*. 101:228-236.

[2] Xiong L., Shamseldin A. Y., and O'Connor K. M., 2001. A non-linear combination of the forecasts of rainfall-runoff models by the first-order Takagi–Sugeno fuzzy system. *Journal of Hydrology*. 245:196-217.

[3] Sanusi Y.K., Ojeniyi A. and Sunmonu L.A., 2015. Application of Artificial Neural Network to Predict Annual Global Solar Radiation for PV System's Sizing in UUM Area, Malaysia. *Proceedings of the International Conference on Electrical and Bio-medical Engineering, Clean Energy and Green Computing*, Dubai, UAE.

[4] Zaw W. T.and Thinn Thu N., 2009. Modeling of Rainfall Prediction over Myanmar Using Polynomial Regression. *in Computer Engineering and Technology. ICCET '09. International Conference on*. 316-320.

[5] Jin L., Zhu J., Huang Y., Zhao H.-s., Lin K.-p., and Jin J., 2015. A nonlinear statistical ensemble model for short-range rainfall prediction. *Theoretical and Applied Climatology.* 119:791-807,

[6] Chang F.-J., Chiang Y.-M., Tsai M.-J., and Shieh M.-C., 2014. Watershed rainfall forecasting using neuro-fuzzy networks with the assimilation of multi-sensor information, J*ournal of Hydrology (Amsterdam)*. 508:374.

[7] Hung N. Q., Babel M. S., Weesakul S., and Tripathi N. K., 2008. An Artificial Neural Network Model For Rainfall Forecasting In Bangkok, Thailand, *Hydrology and Earth System Sciences Discussions*. 5:183-218.

[8] Dani S. and Sharma S., 1996. Forecasting Rainfall of a Region by Using Fuzzy Time Series. *Asian Journal of Mathematics and Application*, vol. 2013, p. 10, 2013.

[9] S.-M. Chen, Forecasting Enrollments Based On Fuzzy Time Series. *Fuzzy Sets and Systems*. 81:311-319.

[10] Chen S. M. and Hsu C. C., 2004. A New Method to Forecast Enrollments Using Fuzzy Time Series. I*nternational Journal of Applied Science and Engineering.* 2:234-244.

[11] Chissom Q. S. B. S. 1993. Fuzzy Time Series and Its Model. Fuzzy Sets and System. 54:269-277.

[12] Domańska D. and Wojtylak M., 2012.Application of Fuzzy Time Series Models For Forecasting Pollution Concentrations. *Expert Systems With Applications*. 39:7673-7679.

[13] Tsaur R.-C. and Kuo T.-C. 2011. The Adaptive Fuzzy Time Series Model With An Application to Taiwan's tourism demand. *Expert Systems With Applications*. 38:9164.

[14] Song Q. and Chissom B. S., 1993. Forecasting Enrollments With Fuzzy Time Series — Part I. *Fuzzy Sets and Systems*. 54:1-9.

[15] Song Q. and Chissom B. S., 1993. Fuzzy time series and its models. *Fuzzy Sets and Systems.* 54:269-277.

[16] Jeng-Ren H., Shyi-Ming C., and Chia-Hoang L., 1998. Handling Forecasting Problems Using Fuzzy Time Series. *Fuzzy Sets and Systems*. 100:217-228.

[17] Sanusi Y.K., Ojeniyi A., and Norani N., 2014. Analysis of Atmospheric Parameters Variation on Effeciency of Polycrystalline PV System in a Tropical Station. *In Applied Mechanics and Materials*. 661:160-167.

[18] Lazim M. A., 2011. Introduction Business Forecasting a Practical Approach, 3th ed. Seri Kembangan, Selangor: U*niversity Publication Center (UPENA),* UiTM.

[19] Zhang G. P. and Qi M., 2005. Neural Network Forecasting For Seasonal And Trend Time Series. *European Journal of Operational Research*. 160:501-514.

[20] Nelson M., Hill T., Remus W., and O'Connor M., 1999. Time Series Forecasting Using Neural Networks: Should The Data Be Deseasonalized First?. *Journal of Forecasting*. 18:359-367.

[21] El-Shafie A. H., El-Shafie, A. El-Mazoghi H. G., Shehata A., and Taha M. R., 2011. A*rtificial Neural Network Technique For Rainfall Forecasting Applied To Alexandria*, Egypt. 6:1306-1316.