TIME SERIES ANALYSIS AND FORECASTING OF FOREST FIRE WEATHER

[1]KANYAPHORN SAKULKITBANJONG, [2]CHUNCHOM PONGCHAVALIT, [3]SAVITRI GARIVAIT

[1,2]Department of Mathematics, Faculty of Science, King Mongkut's University of Technology Thonburi, 10400, Thailand,
[3]The Joint Graduate School of Energy and Environmental, King Mongkut's University of Technology Thonburi, 10400, Thailand
E-mail: [1]fon0243@gmail.com, [2]pchunchom@yahoo.com, [3]savitri_g@jgsee.kmutt.ac.th

Abstract- Forest fire is one of the most dangerous natural hazards around the world which meteorological factors are important for conducting forest fire. This objective is to compare the performances between Autoregressive Integrated Moving Average (ARIMA) and Holt-Winters (HW) models for the forecasting meteorological data including average wind speed, precipitation, temperature pressure and relative humidity in northern Thailand. As performance measures of models by using the minimum Mean Absolute Percentage Error (MAPE). The result showed that the HW model obtained better model with precipitation, pressure and relative humidity data. However ARIMA model appear to the better model with average wind speed and temperature data. Then we fit time series models to forecast meteorological factors year 2015.

Index Terms- Time Series Analysis, ARIMA, Holt-Winter

I. INTRODUCTION

Forest fires can cause damage on natural resources. Meanwhile, it can also bring serious economic and social impacts. As well as forest fire affect the forest amount of greenhouse gasses and aerosols. Meteorological factors play a critical role in establishing conditions favorable for a forest fire. 'Fire weather' which refers to meteorological factors is conducive to forest fire, such as average wind speed, precipitation, monthly temperature, pressure and relative humidity. [1] That is, low relative humidity causes dry combustible materials and hence a high probability of forest fire. Relative humidity has an important impact on forest fires. With higher temperatures, lower precipitation, and/or lower relative humidity promote larger fires (Flannigan and Harrington, 1988) [2].

In Thailand, forest fires occur frequently in the northern part where the risk of forest fire is high from January to April due to the influences of geographical location, topography, climate and forest distribution, Recently, the work of Sakulkitbanjong et al. [3] studied the relationship of forest fire risk under the climates in the northern Thailand during 2010-2014 by using Logistic regression analysis. The results showed that these factors had impact on the risk of forest fires each year differently. Obviously, Meteorological factors characterize in verifying conditions for a forest fire. Therefore Effective prediction of forest fire occurrences could prevent or minimize losses. So, it is feasible and operational to predict forest fire based on the analysis of those meteorological factors. Time series analysis and forecasting have become a major tool in numerous meteorological applications to study trends and variations in environmental parameters [4]. Moreover time series analysis can be investigate its variability pattern and predicting future trends.

Therefore, the objective of the study is to assess of forecasting meteorological data in forest fire occurrence by using time series analysis.

II. METHODOLOGY

Study Area

The study area is the northern part of Thailand which is one of the five regions of the country, covering an area of 93,690 km^2 and bordering Myanmar and Laos. Most of the area is covered by forest, while agricultural activities and residential area cover about 30 % of the total area. There are 8 provinces: Chiang Mai, Chiang Rai, Mae Hong Son, Phrae, Nan, Lampang Phayao, and Uttaradit.

The climate of Northern Thailand is influenced by southwest and northeast monsoons. The southwest monsoon normally starts in May to October resulting the wet weather, while the northeast monsoon usually begins in October to February resulting dry and cool weather over the region[5]. The period from February until the end of May is the transition period, and the hottest weather is observed during March– April, which is known as the local summer. According to Thailand's statistics and causes of forest fires, the most forest fire events are observed in the study area and forest fires occur in March and time of firing ranges between 14.00-16.00 p.m.

The data of meteorological factors (average wind speed, temperature, precipitation, pressure, relative humidity) is derived from the Thai Meteorological Department during 2010-2014 [6].

Statistical analysis

Time series method for analyzing data in this study as follows:

-Holt-Winters method

Holt-Winters method [7] is a extension of the exponential smoothing methodology since it generalizes this methodology to deal with trend and seasonality. It considers as the three smoothing parameters and p denotes the number of observations

per seasonal cycle [13]. It is similar to the linear method of Holt, with an additional equation to deal with seasonality. There are two different methods of Holt-Winters, differing by how the seasonality is modeled, classified as additive and multiplicative. This study will be applied only to the HW multiplicative model. As shown in the following equations:

Index $l_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-} + b_{t-})$ (1)

Trend $b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*) b_{t-1}$ (2)

Seasonality $s_t = \gamma y_t / (l_{t-1} + b_{t-1}) + (1-\gamma) s_{t-m}$ (3)

Forecast $\hat{y}_{t+h/t} = (l_t + b_t h) s_{t-m+h_m^+}$ (4)

Where is the extent of seasonality (such as number of months or quarters in a year), l_t represents the series level, b_t denotes the trend, s_t is the seasonal component, $\hat{y}_{t+h/t}$ is the forecast for h periods ahead and $h_m^+ = [(h-1) \bmod m] + 1$. The parameters ($\alpha, \beta^*$, and γ) are usually restricted to the range 0 to 1.

-ARIMA model [8]

An autoregressive model of order p is classified as AR (p) and a moving average model with q terms is known as MA (q). A combined model contains p AR-terms and q MA-terms is called an ARMA (p, q) model [6]. To make a generally nonstationary time-series stationary time-shifted (by d lags, whereby in most cases d=1) differences are computed before further processing. Such a model is then classified as ARIMA (p, d, q), where the symbol "I" signifies "integrated". Assuming that the original data Y_t has been made stationary by taking d nonseasonal differences (whereby in most cases d=1), an ARMA (p, q) model for this new, stationary time series Yt is as follows:

$$Y = a + \varphi_1 Y_{t-1} + \ldots + \varphi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots \theta_q e_{t-q} \quad (5)$$

Where a = constant term,

φ = autoregressive parameter,

θ = moving average parameter, e_t = the error term at time t.

For climate data which usually follows a seasonal, i.e. an annual cycle, it is more appropriate to use a seasonal ARIMA (p, d, q) (P, D, Q)S model, where P is the order of the seasonal AR-model; D is the order of the seasonal differencing (for monthly data, usually, D= 12) and Q is the order of the seasonal MA-model and s is the number of periods in the season (s=12, for an annual cycle) [7].

The general form of such a seasonal ARIMA (p, d, q) (P, D, Q)S model, can be written in backshift notation as

$$\varphi_{AR}(B)\varphi_{SAR}(B^s)(1-B)^d(1-B^S)^D Y_t = \theta_{MA}(B)\theta_{SMA}(B^s)e_t \quad (6)$$

where φ_{AR} = non-seasonal of AR- parameter,

φ_{SAR} = seasonal of AR-parameter,

θ_{MA} = non-seasonal of MA- parameter,

θ_{SMA} = seasonal of MA- parameter,

B= backward shift operator.

To identify a ARIMA model for a particular time series, Box and Jenkins [6] proposed a methodology that consists of four steps: i) model identification; ii) estimation of the model parameters; iii) diagnostic checking for the identified model appropriateness and iv) forecasting.

As the original monthly temperature time series analyzed here are non-stationary, and have a 12month seasonality, they are all differenced non seasonally at lag d=1 and differenced seasonally at lag D=12.

Then the determination of the orders p and q in ARMA(p,q) model. This is done by investigation of the partial autocorrelation plot and the partial autocorrelation plot of the time series, respectively. Then Maximum Likelihood method is used for estimating parameters of the model.

In step of diagnostic checking model, we used the mean absolute percentage error (MAPE) which the MAPE are the least, is chosen as the appropriate model. [7]. The MAPE can be expressed as follows:

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{E_t}{O_t} \right|}{n} \times 100 \quad (7)$$

Where: E_t = absolute error value in the period t;

O_t = absolute value of observed data in the period t;

n=all the periods.

III. RESULTS

The results from as follow:

- Average Wind Speed

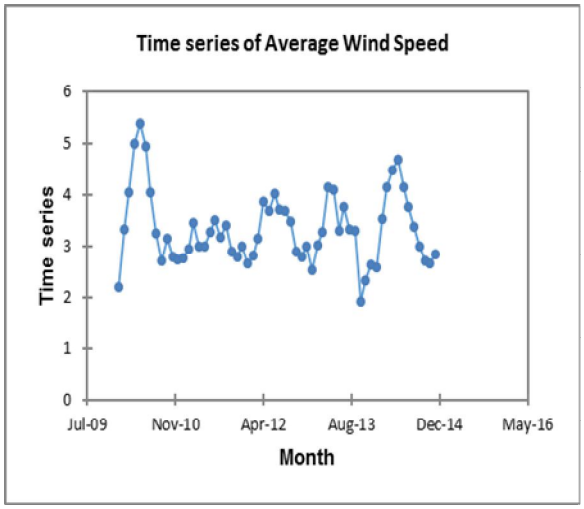


Figure 1 : The time series plot of monthly Average Wind Speed at Northern Thailand from 2010 to 2014

Table 1 Descriptive of monthly Temperature values 2010-2014

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Average Wind Speed(km/s)	60	1.915	5.375	3.331	0.700

The result shows the mean of monthly average wind speed in 2010-2014 (60 months) is 3.331 km/s and the standard deviation is 0.700, minimum of monthly average wind speed is 1.915 km/s and a maximum of monthly average wind speed is 5.375 km/s.

Figure 1 shows a plot of time series data for average wind speed data in northern Thailand (2010-2014). After comparing model, we chose for fitting only the Holt-Winters model. So we chose for fitting only ARIMA model for this data. As Figure 1 shows that there is a clear non-stationary. After differencing, a stationary sequence was obtained, and the order of difference is reflected in parameter d as 1 here. Thus, the time series model of average wind speed can be identified as ARIMA (2, 1, 2), and the equation used for the average wind speed is described as follows:

$Y(t) = 1.675\ X(t-1) - .9427\ X(t-2) + Z(t) - .9849\ Z(t-1) + .3468\ Z(t-2)$, WN Variance = .129199

where Yt denotes the observed value at time t, t = 1, 2, . . . k; and εt is the estimated residual at time t, which should be independently and identically distributed as normal random variables with a mean of zero and a constant variance.

The monthly forecast results of the average wind speed using the ARIMA (2, 1, 2) model for the year 2015 are shown in Table 3 and figure 3.

Table 3: Forecasts of the Average Wind Speed from January-December 2015 using ARIMA (2, 1, 2) model

Month	Forecast	95% Forecasting (Lower, Upper)
January	3.03542	(2.19481, 3.87603)
February	3.14675	(1.84421, 4.44930)
March	3.12772	(1.32604, 4.92939)
April	2.99708	(0.67390, 5.32025)
May	2.82486	(0.02752, 5.62220)
June	2.69626	(-0.47057, 5.86309)
July	2.67070	(-0.74895, 6.09034)
August	2.75549	(-0.82904, 6.34001)
September	2.90566	(-0.80002, 6.61135)
October	3.04834	(-0.77578, 6.87245)
November	3.11868	(-0.85429, 7.09165)
December	3.08987	(-1.08065, 7.26038)

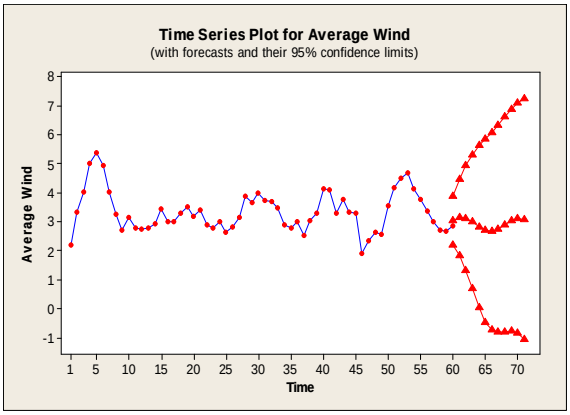


Figure 3: Forecasted of monthly Average Wind Speed at Northern, Thailand in 2015

Therefore ARIMA (2, 1, 2) model appears to be a fit model for average wind speed data.

Temperature

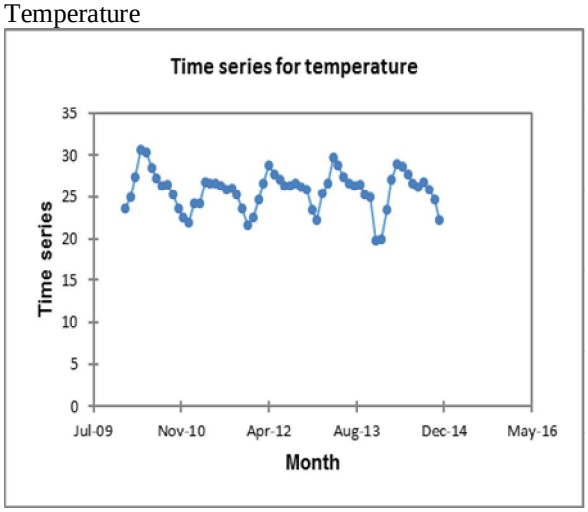


Figure 4: The time series plot of the monthly Temperature at Northern Thailand from 2010 to 2014

Table 4 Descriptive of monthly Temperature data 2010-2014

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Temperature	60	19.813	30.695	25.792	2.324

The result shows the mean of monthly temperature in 2010-2014 (60 months) is 25.792 $^{\circ}C$ and the standard deviation is 2.324 $^{\circ}C$, minimum of monthly temperature is 19.813 $^{\circ}C$ and maximum of monthly temperature is 30.695 $^{\circ}C$. Figure 4 shows a plot of time series data. There is a clear non-stationary, and seasonality. After comparing model, we chose for fitting only the ARIMA model. Then differencing, a stationary sequence was obtained, and the order of difference is reflected in parameter d as 1 here. Thus, the time series model of Temperature can be identified as ARIMA (1, 1, 1)$(1, 1, 1)_{12}$. Following a similar procedure, the ARIMA models were constructed to obtain time series forecasts from January-December 2015 as Table 5 and Figure5.

Table 5: Forecasts of the Temperature from January-December 2015 using ARIMA (1, 1, 1) $(1,1,1)_{12}$ model

Month	Forecast	95% Forecasting (Lower, Upper)
January	22.423	(20.9298, 23.9162)
February	25.0994	(23.3587, 26.8402)
March	26.2494	(24.4094, 28.0894)
April	29.316	(27.4224, 31.2096)
May	28.6309	(26.7009, 30.5609)
June	27.7534	(25.7944, 29.7125)
July	27.1961	(25.2114, 29.1807)
August	26.9629	(24.9544, 28.9713)
September	27.1419	(25.1107, 29.1732)
October	26.3869	(24.3333, 28.4404)
November	25.8537	(23.7783, 27.9291)
December	22.8419	(20.7450, 24.9388)

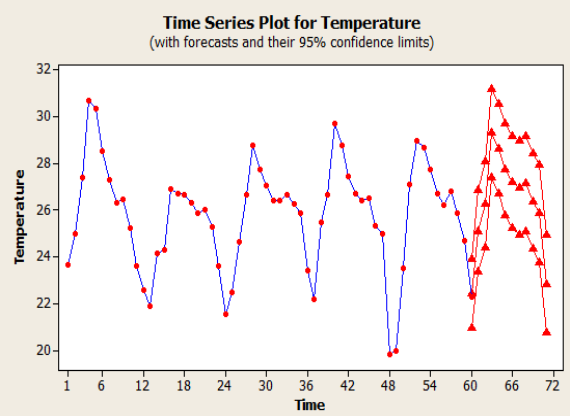


Figure 5 : Forecasted of monthly Temperature at Northern, Thailand in 2015

Considering MAPE values of the ARIMA (1, 1, 1) $(1,1,1)_{12}$ model are lower. Therefore the ARIMA (1, 1, 1) $(1,1,1)_{12}$ model appears to be a fit model for temperature data.

Precipitation

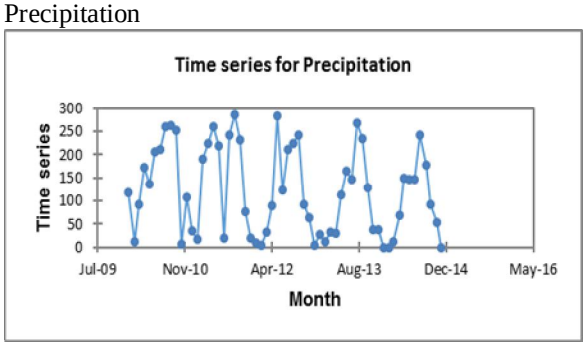


Figure 6 : The time series plot of the monthly Precipitation at Northern Thailand from 2010 to 2014

Table 6 Descriptive of monthly Precipitation data 2010-2014

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Precipitation	60	0.000	285.230	123.157	94.049

The result shows the mean of monthly precipitation in 2010-2014 (60 months) is 123.157 mm. and the standard deviation is 94.049 mm., minimum of monthly Precipitation is 0 mm. and maximum of monthly Precipitation is 285.230 mm. After comparing model, we chose for fitting only the Holt-Winters model. So the monthly forecast results of the monthly Precipitation using the Holt-Winters model for the year 2015 are shown in Table 7.

Table 7: Forecasts of the monthly Precipitation from January-December 2015

Month	Forecast	95% Forecasting (Lower, Upper)
January	18.969	(33.7122, 72.249)
February	5.434	(58.2138, 97.354)
March	36.868	(91.2300, 131.044)
April	73.952	(48.0880, 88.641)
May	140.690	(10.0472, 51.402)
June	123.725	(3.0667, 45.282)
July	108.663	(-2.2714, 40.859)
August	168.729	(-2.8085, 41.290)
September	151.892	(-3.1654, 41.949)
October	91.822	(7.8320, 54.009)
November	31.045	(3.8241, 51.105)
December	15.911	(17.7651, 66.189)

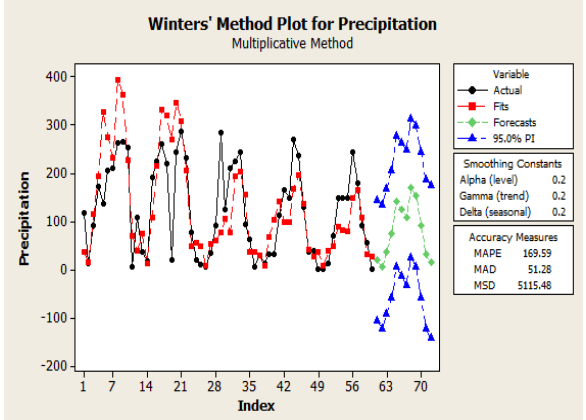


Figure 7: Forecasted of monthly Precipitation at Northern, Thailand in 2015

Considering MAPE values of the Holt-Winters seasonal multiplicative model are lower compared to those model. As such, the Holt-Winters seasonal multiplicative model allows to very well take into account the upward trend, the seasonalities and the increase in variability within a period. Therefore Holt-Winters seasonal multiplicative model appears to be a fit model for precipitation data.

Pressure

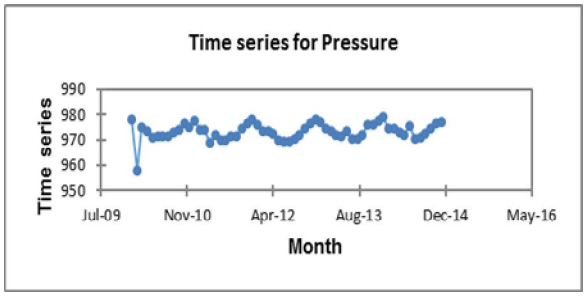


Figure 8: The time series plot of the monthly Pressure at Northern Thailand from 2010 to 2014

Table 8 Descriptive of monthly Pressure data 2010-2014

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Pressure	60	957.560	979.130	973.316	3.338

The result shows the mean of monthly pressure in 2010-2014 (60 months) is 973.316 hPa and the standard deviation is 3.338 hPa, minimum of monthly pressure is 957.560 hPa and maximum of monthly pressure is 979.130 hPa. After comparing model, we chose for fitting only the Holt-Winters model. The forecast results of the monthly Pressure using the Holt model for the year 2003 are shown in Table 9

Table 9: Forecasts of the monthly Pressure from January-December 2015 using the Holt-Winters' model

Month	Forecast	95% Forecasting (Lower, Upper)
January	978.309	(973.908, 982.709)
February	972.001	(967.531, 976.471)
March	974.183	(969.637, 978.730)
April	971.958	(967.327, 976.589)
May	971.153	(966.431, 975.876)

June	971.934	(967.113, 976.754)
July	969.652	(964.726, 974.577)
August	970.412	(965.376, 975.447)
September	971.437	(966.285, 976.589)
October	974.004	(968.731, 979.277)
November	975.398	(969.999, 980.797)
December	976.173	(970.643, 981.702)

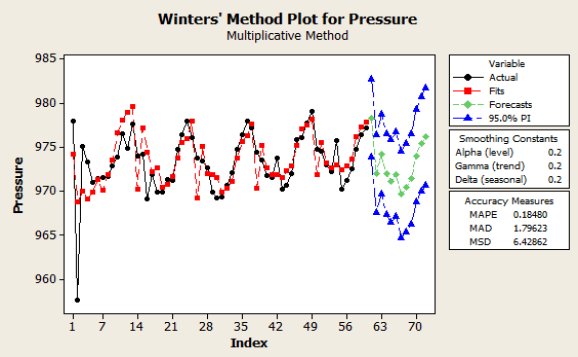


Figure 9: Forecasted of monthly Pressure at Northern, Thailand in 2015

Considering MAPE values of the Holt-Winters seasonal multiplicative model are lower compared to those model. As such, this model allows to very well take into account the upward trend, the seasonalities and the increase in variability within a period. Therefore Holt-Winters seasonal multiplicative model appears to be a fit model for pressure data.

Relative Humidity

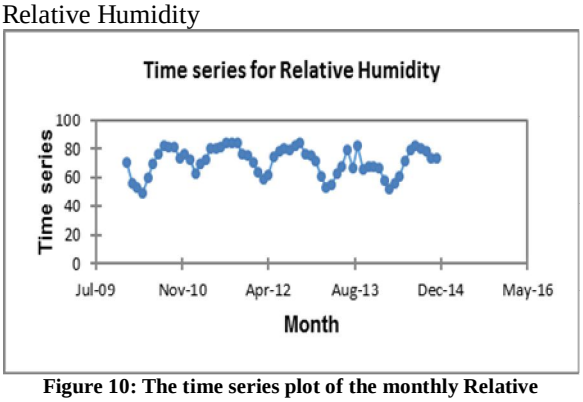


Figure 10: The time series plot of the monthly Relative Humidity at Northern Thailand from 2010 to 2014

Table 10 Descriptive of monthly Relative Humidity data 2010-2014

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Relative Humidity	60	49.250	84.150	71.263	9.621

The result shows the mean of monthly relative humidity in 2010-2014 (60 months) is 71.263% and the standard deviation is 9.621%, minimum of monthly relative humidity is 49.250 % and maximum of monthly relative humidity is 84.150 %. After comparing model, we chose for fitting only the Holt-Winters model. The forecast results of the monthly Relative Humidity using the Holt-Winters seasonal multiplicative model for the year 2015 are shown in Table 11.

Table 11: Forecasts of the Relative Humidity from January-December 2015 using the Holt-Winters model

Month	Forecast	95% Forecasting (Lower, Upper)
January	73.3899	(62.4142, 84.366)
February	63.4666	(52.3189, 74.614)
March	59.9884	(48.6491, 71.328)
April	62.4565	(48.0880, 88.641)
May	72.2404	(50.9066, 74.006)
June	79.1964	(60.4622, 84.019)
July	86.4721	(67.1732, 91.220)
August	85.6364	(74.1880, 98.756)
September	90.2457	(77.3966, 103.095)
October	86.6229	(73.4714, 99.774)
November	82.3879	(68.9219, 95.854)
December	83.2736	(69.4820, 97.065)

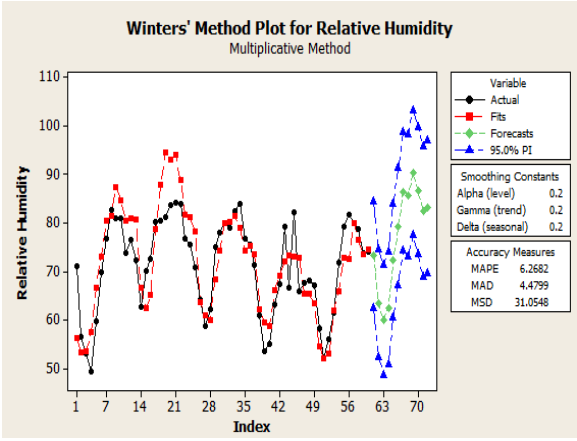


Figure 11: Forecasted of monthly Relative Humidity at Northern, Thailand in 2015

Considering MAPE values of the Holt-Winters seasonal multiplicative model are lower compared to those model. As such, this model allows to very well take into account the upward trend, the seasonalities and the increase in variability within a period. Therefore Holt-Winters seasonal multiplicative model appears to be a fit model for relative humidity data.

CONCLUSION

ARIMA and Holt-Winter model which a statistical analysis model to predict future trends. As well as can be used in this meteorological data for forecasting forest fire in northern Thailand. Meteorological factors are important factors for conducting forest fire in northern Thailand. So This study aimed to assess of forecasting meteorological data in forest fire occurrence by comparison between the Holt-Winters and ARIMA models. The results showed that time series of average wind speed and temperature are fitted by the ARIMA model. For Holt-Winter model obtained better results in precipitation, pressure and relative humidity data. Thus The ARIMA and Holt-Winters model can provide accurate forecasting results. as those obtained with more complex techniques. Moreover this method is popular, easy to use and generally works well in practical applications can help decision makers to establish better strategies and to make decision or risk assessment.

ACKNOWLEDGEMENTS

This work was supported by the Science Achievement Scholarship of Thailand (SAST) and National Research University (NRU) Project of Thailand, Office of Higher Education Commission.

REFERENCES

[1] AL. Westerling, HG. Hidalgo, DR. Cayan, Swetnam TW. "Warming and Earlier Spring Increase WesternU.S." Forest Wildfire Activity". Science. Vol. 13: pp.940–943, 2006.

[2] M. D. Flannigan, and J. B. Harrington. "A Study of the Relation of Meteorological Variables to Monthly Provincial Area Burned by Wildfire in Canada". Journal of Applied Meteorology. vol.27: pp.441-452, 1988.

[3] K. Sakulkitbanjong, A. Pongpullponsak, S. Garivait, C. Pongchavalit. "Comparison of Forest Fire Risk by Using K-Means Clustering Analysis" ICAS, Thailand, 2015.

[4] S.A. Shamsnia, N. Shahidi, A. Liaghat, A. Sarraf and S.F. Vahdat. 2011. Modeling Of Weather Parameters (Temperature, Rainfall And Humidity) Using Stochastic Methods. Internat. Conference on Environment and Industrial Innovation, IPCBEE, Singapore, pp.282-285.

[5] Kim Oanh, N. T., Piromyaporn, C., Ekbordin, W., & Wangwongwatana, S. (2005). "Meteorological pattern classification and application for forecasting air pollution episode potential in a mountain-valley area. Atmospheric Environment" vol.39, pp.1211 –1255, 2005.

[6] Thailand Meteorological Department ,http://www.tmd.go.th/en/archive/thailand_climate.pdf (accessed on November 30th, 2015)

[7] R. J. Hyndman, A. B. Koehler, J. K. Ord, Snyder, R. D. Snyder. "Forecasting with exponentials moothing: the state space approach, Germany" Springer. 2008, Vol. 351, pp. 13, 2008.

[8] G.E.P. Box and G.M. Jenkins. 1976. Time Series Analysis: Forecasting and Control. Revised Edn.,Holden-Day, San Francisco, CA. 1976.

★★★