ISBN 978-81-933894-3-0
5th International Conference on Urban Planning, Transport and Construction Engineering (ICUPTCE'17)
Pattaya (Thailand), May 2-4, 2017

Time Series Analysis for Home Furniture Delivery and Assembly Service in Indonesia and Thailand

Tangguh Wicaksono and Somchai Pathomsiri

Department of Civil and Environmental Engineering, Faculty of Engineering, Mahidol University

***Abstract*:** *Forecasting is one of crucial problem that is confronted all industries, especially for Home Delivery and Assembly Service (HFDAS). A better operational planning is initiated by the appropriate forecast demand. In this research, although the HFDAS providers have been operated over one year, the logistic providers have not implemented any of the appropriate forecasting methods as their demand planning. Hence, the provider has no preparation to anticipate the increasing of demand that caused the higher transportation cost about 54% of total cost in 2015. The daily demand forecasting is suggested in order to provide the operational guideline such as the number of employees, number of trucks, equipment, warehouse capacity and future demand anticipation. This paper attempts to predict the daily demand by using time series analysis including short-term and long-term forecasting. The time series forecasting methods include naïve, moving average, exponential smoothing, Holt-Winters and ARIMA methods. The comparison of accuracy measurements is studied in order to determine the best forecasting method for both countries. According to the accuracy measurements, Holt-Winters method were selected as the best method for short-term and long-term forecasting daily demand in Jakarta and Bangkok. Finally, dynamic forecasting is recommended to yield a better result.*

Keywords: *Daily demand, Time series analysis, Seasonality factors, Holt-Winters methods, Accuracy measurements comparison*

1. Introduction

Demand forecasting is one of the most important factor that is highlighted in any organizational and enterprise level. By predicting the future demand, the company can prepare several strategic, operational and planning decisions in order to reduce the waste of outcome. For example, the sales forecasting helps the retail business to manage their production, purchasing, transportation and labor force [1]. The more accurate forecasting also can minimize the bullwhip effects in supply chain. The forecasting of airport passenger is an indication for the stakeholders to improve the performance by preparing the scenario analysis. Indeed, the demand of electricity and heat load forecasting successfully reduce the environment impact in terms of energy [2]. The implementation of accurate forecasting affects the operational efficiency and avoids the negative impacts of future demand. This research uses the realistic case of a home furniture delivery and assembly service (HFDAS) which receives the various furniture products from the customers. The services are to deliver furniture components, kitchen installation and curtain sewing products from the Home Furnishing Company store and distribute to customer locations across the service zones. Not only in Jakarta, Home Furnishing Company Bangkok also outsourced the delivery service to the third-party logistic (3PL) company. Based on key performance indicators report, the HFDAS provider in Jakarta confronted the delayed and rescheduled complaints almost one order per day during January-September 2015. This situation caused the higher transportation cost about 54% of total cost in 2015. Concurrently, the suddenly increasing of demand during 25-31 December 2015 was occurred due to the 15,000 baht tax deduction by Bangkok's government, as a gift for the people [3]. This scheme enacted HFDAS providers business, then it is called bullwhip phenomenon.

Unfortunately, the research that emphasized the furniture industry and supply chain management issues with respect to home furniture delivery and assembly service are not comprehensively carried out.

The major contributions of this paper consist of threefold. First, this paper is believed as the first attempt to study the demand forecasting for home furniture delivery and assembly service in Jakarta and Bangkok. Second, the forecasting of daily demand was analyzed by using time series analysis in order to anticipate the future demand. Mostly, previous researches addressed in the manufacturing and energy industry case studies which solved the problems of demand planning in term of electricity price, heat load, telecommunications, tourism demand, population, passengers of airline and truck sales [4,5]. The best forecasting method and peak period can be identified as the preparation planning to anticipate the forecast daily demand. The historical of applications and relevant researches about home furniture delivery and assembly service have been reviewed from the past to the recently researches in Section 2. Several forecasting methods are explained in the Section 3. However, case study and time series analysis are described in the section 4. Finally, section 5 includes the conclusion and further research.

2. Literature Review

2.1. The Characteristics of Home Furniture Delivery and Assembly Service

Basically, the home furniture delivery and assembly service has the similar issues which are faced by other home delivery services or last mile delivery. These pertain in delivery time, packaging, loading, facility expansion, the reverse logistic and bullwhip phenomenon. In terms of truck loading problem, Hostetler [6] indicated the inefficiency of the packaging and loading sequences problem for home delivery service of truck. The findings by Morganti et al. [7] showed that the ongoing explosion of demand in home delivery service forced the Amazon and Zalando Company to expand and establish new facility, in particular for being a distribution centre. Furthermore, several researches visualize the current operation activities such as food distribution centre [8], warehouse management with lean [9] and warehouse analysis [10].

2.2. Forecasting Demand by Using Time Series Data Analysis

Many researches developed forecasting methods to yield as accurate as results. For retail sales or department store, the study by Geurts & Kelly [11] categorized the forecasting techniques of department store into three methods including judgmental, econometric and time series. Judgmental method is normally used when the historical data is unavailable. Hence, the judgmental method is more popular in terms of new product/service forecasting [11, 12, 13]. Otherwise, the econometric and time series methods are frequently used to forecast existing sales due to the availability of historical data. In addition, the extra cost must be prepared also to collect the independent variable data such as economic variables and income level data [11,14]. Otherwise, time series method tends to have less cost, simplicity and accuracy to be implemented that basically used only the previous sales data. Finally, the findings by Groff [15], Schmidt [16] and Geurts & Kelly [11] postulated that the time series outperformed econometric forecast. In term of extrapolation or time series, several researches utilized the historical data as the database to build the forecasting models. The one well-known method is Holt-Winters method which considers three parameters including level, trends and seasonality term. Before implementing the Holt-Winters method, Chatfield & Yar [17] investigated three main practical issues that are faced in the Holt-Winters method including the normalization of seasonal indices, determination of starting values and the choice of smoothing parameters. Lawton [18] examined the basic additive form of Holt-Winters method and improved the quality of estimates by using the correction method. The spreadsheet tested two case studies including monthly passengers of airline and quarterly demand of chemical company. The research by Tratar & Strmcnik [2] compared the 16 time series forecasting techniques by using heat load data from case studies. Each technique is tested to forecast the daily, weekly and monthly demand of heat load with parameters (alpha, beta and gamma) by using Solver function in Microsoft Excel. The one of popular time series forecasting techniques is the Box-Jenkins method, especially for univariate method. Auto regressive-integrated-moving average (ARIMA) model is a general stochastic process that was introduced by Box-Jenkins in 1970 [19]. Both Holt-Winters and ARIMA methods are usually compared to select an appropriate forecasted demand. Many researches attempt to test the ability of Holt-Winters and ARIMA method to predict the future demand including Chatfield [19], Chatfield & Yar [17] and Bianchi et al. [20]. The study by Chatfield [19] suggested to apply the Holt-Winters method for series in which the variation follows the trend and seasonal.

Based on the previous research, it was found that most researchers focused on retail sales, manufacturing and energy industry case studies which solved the problems of demand planning. The applications include electricity price, telecommunications, tourism demand, population and truck sales [5]. Only a few researchers focused on the forecasting in the home furniture delivery and assembly service. In the current study, the company has never prepared for the future demand that is very important to plan the required supply. Hence, this paper attempts to apply five forecasting techniques of time series including naïve forecasting method, moving average, simple exponential smoothing, Holt-Winters forecasting and ARIMA methods in order to estimate the daily demand. Finally, the accuracy of individual methods are compared by using mean absolute error, mean absolute percentage error and U-statistics in order to select the most accurate results.

3. Methods

3.1. Forecasting Techniques

- Naïve forecasting method

Generally, the naïve method is the simplest way to forecast the daily demand. Aneiros et al. [21] used the naïve method to forecast the daily demand of electricity. The historical data is highly required because it is assumed that the forecasted demand ($\hat{Y}_{t+1}$) is equal to the demand at previous period (Y_t) [2,13].

$$\hat{Y}_{t+1} = Y_t \tag{1}$$

- Moving average

The moving average has a simple calculation based on time series. Let Y_t be the value of previous or actual demand at period $_t$ and $\hat{Y}_{t+1}$ is the forecast demand during period $_{t+1}$. The parameter N denotes the number of periods which should be less than $_{t+1}$ [13,22].

$$\hat{Y}_{t+1} = \frac{\sum_{i=1}^{N} Y_{t-i+1}}{N} \tag{2}$$

- Simple exponential smoothing

The exponential smoothing is useful to estimate the demand if the historical data follow the base level. Let α be a smoothing constant that satisfies 0< α < 1. The value of $\hat{Y}_t$ denotes the previous forecast demand during period $_t$. Y_t is defined as actual demand during period $_t$. The notation $\hat{Y}_{t+1}$ represents forecast demand during period $_{t+1}$.

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_t \tag{3}$$

- Holt-Winters forecasting method

The Holt-Winters method is adopted if the historical data have the trend and seasonality. Generally, the models consist of level factor (L_t), trend factor (b_t), seasonality factor (S_t) and forecast daily demand ($\hat{Y}_{t+1}$). There are two computation types that can be used in Holt-Winters methods including multiplicative and additive [2,13]. The formulations of multiplicative Holt-Winters method are shown below.

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{4}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{5}$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{6}$$

$$\hat{Y}_{t+m} = (L_t + b_t m)S_{t-s+m}, t \geq s, m \geq 1, \alpha, \beta, \gamma \in (0,1) \tag{7}$$

Where m denotes the number of forecast ahead, s represents the length of seasonality and Y_t defines the observed demand during period $_t$. In the Holt-Winters method, the three smoothing parameters are used i.e., α associated with level, β associated with trend and γ associated the seasonality. The equation (4) denotes the level of time series at period t by dividing Y_t with the seasonal indices (S_{t-s}). The equation (5) represents the trend (b_t) among L_t that is adopted from Holt's method. Seasonality factor is computed by using equation (6) which is generally following the exponential smoothing method. The forecast daily demands are estimated by computing equation (7). Furthermore, the both Holt-Winters methods can also be applied to the data series that have no trend by eliminating trend factor [13]. There are four different Holt-Winters methods that are examined in this research including multiplicative, additive, multiplicative without trend and additive without trend.

- ARIMA method

There are four stages procedure in the ARIMA model including identification, estimation, evaluation and prediction [23]. In the practice, the data series must be the stationary data series to build the model. In the identification step, the data series will be assessed to check the non-stationary data series, including trend and seasonal pattern. The natural logarithmic and differencing may be transformed to data series in order to stabilize the variance and mean [1,23,24]. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are analyzed and plotted in order to identify the degree of differencing. The second step in identifying the stationarity of series is to use a statistic test to examine the unit root of dataset. Following to Washington et al. [25], the well-known statistic test for unit root test is Augmented Dickey-Fuller (ADF) test. In the model estimation, there are two main steps including ordinary least square and Akike Info Criterion (AIC). The coefficients of model are determined by using the ordinary least square or linear regression method. Box et al. [23] suggested compiling the maximum likelihoods. The residuals must satisfy the "white noise" requirements. The white noise obligates the residuals are distributed normal and independent. In this step, Tsui et al., [24] recommended to conduct the Box-Ljung test to ensure the residuals are independent. The last step is forecasting process which can be used to predict the m-step ahead forecasts. For example, the ARIMA(1,1,1) model structure is formulated below.

$$\hat{Y}_t = c + (1+\emptyset_1)Y_{t-1} - \emptyset_1 Y_{t-2} + \theta_1 e_{t-1} + e_t \tag{8}$$

Where Y_t denotes the dependent variable or the actual demand at period t. The symbol $\emptyset_p$ represents the coefficient of each lag (Y_{t-p}) which also is defined as the finite set of weight parameter. Meanwhile, the e_t denotes the error term at period t. The notation θ_q denote the coefficient of error at period q.

3.2. Accuracy Measurements

There are several techniques to measure the results of forecasting techniques including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and U-statistics (U-stat). The smallest number is suggested as the best technique that can be applied to predict the future demand.

$$MAE = \frac{\sum_{t=1}^{N} |Y_t - \hat{Y}_t|}{N} \tag{9}$$

Mean absolute error is the summation of absolute value of gaps between observed or actual demand (Y_t) and forecast demand ($\hat{Y}_t$) during period t divided by number of samples (N). The next accuracy measurement is mean absolute percentage error.

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} |100\frac{Y_t - \hat{Y}_t}{Y_t}|\% \tag{10}$$

MAPE compares the value of errors with the forecasted daily demand in order to get the percentage of error. In addition, Theil's U-statistics is often calculated to measure the forecasting accuracy.

$$U - Stat = \sqrt{\frac{\sum_{t=1}^{n-1}(\frac{\hat{Y}_{t+1} - Y_{t+1}}{Y_t})^2}{\sum_{t=1}^{n-1}(\frac{Y_{t+1} - Y_t}{Y_t})^2}} \tag{11}$$

Where U-statistics is computed through observed or actual daily demand (Y_t andY_{t+1}) and forecasted daily demand ($\hat{Y}_{t+1}$). For U-statistics, the value less than 1 indicates the more accurate forecasting results.

4. Results and Discussion

4.1. Case Study

Home Furnishing Company outsourced the home furniture delivery and assembly service (HFDAS) to a logistic provider in Bangkok and Jakarta. HFDAS Bangkok has more experiences for serving the customers because they have been launched since 2011. However, the HFDAS Jakarta has been launched since 2014. There are many variants of product sizes that are vended at Home Furnishing Company. Mostly, the customers bring products back home by using their own private cars with its limited space, especially for small product size. Hence, Home Furnishing Company outsourced a third party logistic (3PL) to serve the customers whom consider to deliver their big size products, so-called home furniture delivery and assembly service (HFDAS). The daily demand is required to be forecasted in order to prepare the operational of warehouse and transportation activities. The data from the customer relationship management during January 2015 to July 2016 have been collected from HFDAS providers in Jakarta and Bangkok.

4.2. Time Series Analysis

The HFDAS Bangkok can serve in average 134 customers per day. However, the HFDAS Jakarta received 47 customers per day during 2015. This number influences the warehouse capacity and number of trucks. The daily demand of both HFDAS are analyzed by comparing the patterns of demand during January to December in 2015. Table 1 summarizes the descriptive statistics on the daily demand, volume of orders and weight of orders.

TABLE I: Descriptive Statistics of Samples, 2015

Statistics	Bangkok			Jakarta		
	Demand (customers)	Volume (m^3)	Weight (kg)	Demand (customers)	Volume (m^3)	Weight (kg)
Minimum	30.00	18.53	2,067.84	9.00	5.83	1,350.52
Maximum	472.00	280.06	63,766.51	134.00	137.00	20,246.36
Mean	134.45	95.89	22,299.77	47.86	28.93	7,419.77
Median	103.00	84.26	19,709.44	33.50	19.63	5,907.60
Std. deviation	60.80	39.21	8,991.03	904.70	547.14	140,250.77

- Modelling data

Training dataset is utilized for method learning. Whilst, to examine the time series forecasting ability, the testing data set are prepared. The actual daily demand were collected during January 2015-May 2016 (n = 512) as the training dataset to forecast the future demand. Therefore, the testing data use the actual daily demand during June 1st-July 31st 2016 (n = 61). Finally, the forecast demands are distinguished based on two horizons; i.e., short-term and long-term forecasting. In terms of short-term forecasting horizon, the forecast daily demand ($\hat{Y}_{t+m}$) one day (m=1) ahead is calculated for each forecasting method. Meanwhile, the forecast demand seven days (m=7) ahead are computed in case of long-term forecasting horizon. Particularly, the alpha, beta, and gamma in Holt-Winters method are obtained by using the *Microsoft Excel's solver*. The value of parameters is shown in Table 2.

TABLE II: Summary of Parameters

No	Forecasting method	Parameters	
		Jakarta	Bangkok
1	Naïve forecasting method	-	-
2	Moving average method	(N = 8)	(N = 8)
3	Simple exponential smoothing	(α = 0.04)	(α = 0.113)
4	Multiplicative Holt-Winters	(s = 7, α = 0.069, β = 0.041, γ = 0.364)	(s = 7, α = 0.158, β = 0.03, γ = 0.384)
5	Multiplicative Holt-Winters without trend	(s = 7, α = 0.006, γ = 0.357)	(s = 7, α = 0.001, γ = 0.372)
6	Additive Holt-Winters	(s = 7, α = 0.094, β = 0.12, γ = 0.376)	(s = 7, α = 0.224, β = 0.074, γ = 0.389)
7	Additive Holt-Winters without trend	(s = 7, α = 0.036, γ = 0.352)	(s = 7, α = 0.067, γ = 0.386)
8	ARIMA	ARIMA(1,0,1)(1,0,1)$_7$	ARIMA(4,1,2)(2,0,2)$_7$

The characteristics of series can also be seen by investigating the parameters in Holt-Winters method. The seasonal factor dominates the patterns of demand based on the gamma more than 0.3 or 30% from the previous actual demand. Moreover, HFDAS Jakarta and Bangkok derives the smallest errors when applies ARIMA. The comparison of accuracy measurement for both HFDAS Jakarta and Bangkok is shown in Table 3.

TABLE III: Comparison of the Training Dataset Accuracy Measurements

No	Forecasting method	Jakarta			Bangkok		
		MAE	MAPE	U-STAT	MAE	MAPE	U-STAT
1	Naïve forecasting	23.025	58.13%	1	45.250	36.15%	1
2	Moving average	24.158	59.34%	0.838	48.358	37.82%	0.826
3	Simple exponential smoothing	25.318	63.71%	0.921	51.847	41.19%	0.878
4	Multiplicative Holt-Winters	13.309	31.53%	0.733	30.635	23.09%	0.678
5	Multiplicative Holt-Winters without trend	12.359	30.14%	0.703	28.594	21.97%	0.679
6	Additive Holt-Winters	13.401	33.36%	0.746	30.681	24.20%	0.694
7	Additive Holt-Winters without trend	12.292	29.85%	0.702	28.325	21.79%	0.662
8	ARIMA	12.207	30.25%	0.455	26.55	20.93%	0.632

- Forecasting results

For short-term forecasting, the one day ahead ($\hat{Y}_{512+m}$, m = 1) forecast daily demand was compared to the actual daily demand on June 1st-July 31st, 2016 (n=61). Principally, the short-term approach is updated every day after one-day operation. For example, the training dataset is added from 512 days to be 513 days after operation on June 1st, 2016. Table 4 shows the short-term accuracy measurements comparison.

TABLE IV: Comparison of the Short-Term Forecasting Accuracy Measurements (m=1)

No	Forecasting method	Jakarta			Bangkok		
		MAE	MAPE	U-STAT	MAE	MAPE	U-STAT
1	Naïve forecasting	22.639	47.53%	1	43.918	29.64%	1.000
2	Moving average	24.456	49.13%	0.841	50.074	32.28%	0.923
3	Simple exponential	23.940	46.48%	0.853	52.576	33.52%	0.970
4	Multiplicative Holt-Winters	12.987	26.90%	0.506	23.353	15.24%	0.480
5	Multiplicative Holt-Winters without trend	12.896	25.87%	0.501	20.966	13.42%	0.444
6	Additive Holt-Winters	13.127	28.14%	0.528	24.168	16.24%	0.510
7	Additive Holt-Winters without trend	12.750	25.97%	0.497	21.740	14.08%	0.462
8	ARIMA	14.429	24.77%	0.466	25.59	15%	0.519

Table 4 showed that the Additive Holt-Winters without trend method provided the best results to estimate the short-term daily demand in Jakarta. Meanwhile, the multiplicative Holt-Winters without trend method is determined as the most accurate method in HFDAS Bangkok. For longer period like one week ahead, the data is applied in order to examine the full period of seasonality (s=7). According to Table 5, it can be concluded that Holt-Winters forecasting method is the best method to forecast the long-term daily demand (m = 7) for HFDAS Jakarta and Bangkok. Finally, this research postulated the finding by Geurts and Kelly [11] that the Holt-Winters method outperformed the ARIMA method in terms of forecasting for department stores sales.

TABLE V: Comparison of the Long-Term Forecasting Accuracy Measurements (m=7)

No	Forecasting method	Jakarta			Bangkok		
		MAE	MAPE	U-STAT	MAE	MAPE	U-STAT
1	Naïve forecasting	25.361	38.70%	1.053	57.770	33.34%	1.216
2	Moving average	24.758	48.53%	0.865	50.676	31.59%	0.953
3	Simple exponential smoothing	24.720	37.62%	0.898	46.272	25.98%	0.926
4	Multiplicative Holt-Winters	13.699	28.57%	0.558	28.806	18.62%	0.609
5	Multiplicative Holt-Winters without trend	12.950	25.95%	0.504	20.982	13.43%	0.444
6	Additive Holt-Winters	14.180	32.00%	0.566	32.705	22.08%	0.689
7	Additive Holt-Winters without trend	13.021	26.61%	0.512	22.804	14.82%	0.486
8	ARIMA	31.082	60.30%	1.12	66.08	43%	1.394

- Comparison of static and dynamic forecasting

In this paper, two results have been compared by involving the fixed and rolling parameters. The parameters are obtained once by using training dataset (n=512 days) in terms of fixed parameters in Table 3; namely, static forecasting. Meanwhile for dynamic forecasting, the parameters are updated regularly according to the length of *m*-step ahead. Two months data during June-July 2016 from HFDAS Jakarta are used to compare the accuracy measurements between static and dynamic forecasting. The comparison of static and dynamic forecasting in Jakarta is shown in Table 6.

TABLE VI: Comparison of the Static and Dynamic Accuracy Measurements in Jakarta (m=1, n = 61 days)

No	Forecasting method	Static		Dynamic	
		MAE	MAPE	MAE	MAPE
1	Multiplicative Holt-Winters	12.987	26.90%	12.87	25.89%
2	Additive Holt-Winters	13.127	28.14%	12.652	25.89%
3	ARIMA	22.260	36.98%	13.236	27.04%

Based on Table 6, the dynamic forecasting yields more accurate result than static forecasting. The main reason is that the static forecasting is computed by using very old data. For instance, the parameters are obtained by using 512 days data, then after one-day operation, the parameters are updated by using 513 days data. For static forecasting, multiplicative Holt-Winters method has smallest MAE of 12.987. Meanwhile for dynamic forecasting, Additive Holt-Winters obtains smallest MAE of 12,652. Hence, it can be concluded that dynamic forecasting is recommended to predict the daily demand of HFDAS provider.

5. Conclusions

This paper portrays the daily demand forecasting for home furniture delivery and assembly service providers in Jakarta and Bangkok. Several methods have been conducted in the time series data analysis. The time series analysis of HFDAS providers were computed by naïve method, moving average, simple exponential smoothing, Holt-Winters and ARIMA forecasting methods. According to the datasets, several findings can be concluded. First, the parameters of all methods were determined in order to select the most appropriate forecasting by using training dataset. The patterns of actual demand were also analysed which generally showed the seasonality. The greater demand will occur on the weekend. The second finding is that the demand patterns have been changed from additive to multiplicative series. During January 2015-May 2016, the actual demand tends to have additive series. Meanwhile, the testing dataset has the multiplicative series during June 1st-July 31st, 2016. For the third finding, the smaller value of *m* in the *m*-step ahead yields the precise forecasting results. It was investigated by using *m*-steps ahead comparison in testing dataset. For the fourth finding, the dynamic forecasting provides more accurate forecasting as compared to static forecasting. The last finding is that the Holt-Winters method is selected as the appropriate forecasting for both HFDAS Jakarta and Bangkok. Due to the orders will be delivered within two days, it can be identified that the transportation activity is more active during weekday. This condition perhaps could be considered as serious concern from the management's perspective. By forecasting the daily demand, the company can prepare the required additional workers, fleets and equipment more efficient and effective. For the further research, if there are additional studies, it will be possible to discover more problems when the new distribution centre is established. Finally, the impact of forecast demand can be analysed deeper by proposing the strategies.

6. Acknowledgements

The authors would like to thank Mr. Suratin Tunyaplin, the management of M-Global Group, the HFDAS Company in this research for the permission to collect the data and the constructive comments. We gratefully acknowledge research equipment and facility support from the Transportation, Traffic and Logistics EXpert Center (T-LEX), Department of Civil and Environmental Engineering, Faculty of Engineering, Mahidol University.

7. References

[1] Ramos, P., Santos, N. and Rebelo, R., "Performance of state space and ARIMA models for consumer retail sales forecasting," *Robotics and Computer-Integrated Manufacturing*, vol. 34, pp. 151–163, 2015.

[2] Tratar, L. and Strmčnik, E., "The comparison of Holt–Winters method and multiple regression method: A case study.*Energy*, vol.109, pp. 266–276, 2016.

[3] Bangkok Post, (2015) *Tax deduction for New Year shoppers*. December 2015. Available: http://www.bangkokpost.com/news/general/804080/tax-deduction-for-new-year-shoppers. Accessed 3 February 2016

[4] Segura, J.V. and Vercher, E., "A spreadsheet modeling approach to the Holt–Winters optimal forecasting," *European Journal of Operational Research*, vol. 131(2), pp. 375–388, 2001.

[5] De Gooijer, J.G. and Hyndman, R.J., "25 years of time series forecasting," *International Journal of Forecasting*, vol. 22, pp. 443–473, 2006.

[6] Hostetler, S, "Determining Package Locations for Delivery Constrained Truck Loading Utilizing Shelves," in *Proceedings of the 2010 Industrial Engineering Research Conference A. Johnson and J. Miller*., 2010.

[7] Morganti, E., Seidel, S., Blanquart, C., Dablanc, L. and Lenz, B., "The impact of e-commerce on final deliveries: Alternative parcel delivery services in France and Germany," *Transportation Research Procedia*, vol. 4, pp. 178–190, 2014.

[8] Gopakumar, B., Sundaram, S., Wang, S., Koli, S., and Srihari, K., "A simulation based approach for dock allocation in a food distribution center," in *Proceedings of the 2008 Winter Simulation Conference*., 2010, pp. 2750-2755.

[9] Chen, J.C., Cheng, C.-H., Huang, P.B., Wang, K.-J., Huang, C.-J., and Ting, T.C., "Warehouse management with lean and RFID application: A case study." *The International Journal of Advanced Manufacturing Technology*, vol. 69(1-4), pp. 531–542, 2013.

[10] Dotoli, M., Epicoco, N., Falagario, M., Costantino, N., and Turchiano, B., "An integrated approach for warehouse analysis and optimization: A case study," *Computers in Industry*, vol. 70, pp. 56–69, 2015.

[11] Geurts, M.D. and Patrick Kelly, J., "Forecasting retail sales using alternative models, *International Journal of Forecasting*, vol. 2(3), pp. 261–272, 1986.

[12] Kahn, K., "An exploratory investigation of new product forecasting practices," *Journal of Product Innovation Management*, vol. 19(2), pp. 133–143, 2002.

[13] Christou, I.T., *Quantitative methods in supply chain management*. London: Springer, 2011, ch.2, pp. 139-202.

[14] Smyth, D.J., "Short-run macroeconomic forecasting: The OECD performance," *Journal of Forecasting*, vol. 2(1), pp. 37–49, 1983.

[15] Groff, G.K.,"Empirical comparison of models for short range forecasting," *Management Science*, vol. 20(1),pp. 22–3,1973.

[16] Schmidt, J.R., "Forecasting state retail sales: Econometric vs. Time series models," *The Annals of Regional Science*, 13(3), pp. 91–101, 1979.

[17] Chatfield, C. and Yar, M., "Holt-Winters forecasting: some practical issues," *The Statistician*,37(2), pp. 129-140,1988.

[18] Lawton, R., "How should additive Holt–Winters estimates be corrected?,".*International Journal of Forecasting*, vol. 14(3), pp. 393–403, 1998.

[19] Chatfield, C., "The Holt-Winters forecasting procedure," *Applied Statistics*, 27(3), pp. 264-279, 1978.

[20] Bianchi, L., Jarrett, J. and Choudary Hanumara, R., "Improving forecasting for telemarketing centers by ARIMA modeling with intervention," *International Journal of Forecasting*, vol. 14(4), pp. 497–504, 1998.

[21] Aneiros, G., Vilar, J. and Raña, P., "Short-term forecast of daily curves of electricity demand and price," *International Journal of Electrical Power & Energy Systems*, vol. 80, pp. 96–108, 2016.

[22] Winston, W.L. and Goldberg, J.B., *Operations research (ISE): Applications and Algorithms*. 4th edition. United States :Thomson Brooks/Cole, 2003 ch. 24, pp. 1275-1335.

[23] Box, G.E.P., Jenkins, G.M. and Reinsel, G.C., *Time series analysis: Forecasting and control*. 4th edition. United States: John Wiley & Sons, 2008.

[24] Tsui, W.H.K., Ozer Balli, H., Gilbey, A. and Gow, H., "Forecasting of Hong Kong airport's passenger throughput," *Tourism Management,* vol. 42, pp. 62–76, 2014.

[25] Washington, Simon P., Karlaftis, Matthew G. and Mannering, Fred L., *Statistical and econometric methods for transportation data analysis*. 2nd edition. United States: Chapman & Hall/CRC, 2010, ch. 8, pp. 207-231.