Decision Support System for Customer Demand Forecasting and Inventory Management of Perishable Goods

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Abstract— **The objective in this research is to study of the decision support system for customer demand forecasting and inventory management of perishable goods. In the present, the company is very competitive. Many companies try to save the cost of production. In addition, the inventory management is important to decrease the cost too. There are many spoiled food businesses in Thailand. Because of Thailand is an agricultural country. The forecasting model is created to apply in planning the quantity of goods to the warehouse for the lowest volume of storage. A wholesale and retail sale of pork chop at Bungkan province is tested in this research. The training sets are the volumes of pork chop in the past 350 days for the forecasting model. The experiment results found that the single exponential smoothing algorithm is higher than the adaptive-response-rate single exponential smoothing algorithm and the Holt's two-parameter linear exponential smoothing algorithm. Then the single exponential smoothing algorithm is selected to create the decision support system for customer demand forecasting and inventory management of perishable goods (DSS_DF&IM) model. In addition, this model can make profit more than the old system that this model gives equal 120,320 Baht while the old system is 99,950 Baht. Moreover, the DSS_DF&IM model can decrease inventory balance more than the old system that is 224 kilograms.**

Index Terms*— Electronic file, *instructions, preparing paper, template

I. Introduction

Current competitive environment in the business world influences supply chain optimization driven by customer demand. A good management system needs to respond for local, regional and global markets quickly. Market mechanisms are attracted by the need to provide the required services. If business cannot find products that will meet your need will ruin your market share [1].

Forecasting can be used to help schedule the current resource usage and will know that how the resources of the organization are used in each day. In addition, agricultural produce requires effective control because this product is shorter than general product. If there is a lot of stockpiling that needs to buy. Then it will cost the owner unnecessarily. The owner cannot know the daily needs of customers. Ordering short-lived or perishable goods is sold to customers, so there is a risk of loss if the product is not sold.

Nowadays, small and medium businesses play a key role in the Thai economy, with 2.65 million SMEs nationwide. SMEs generate economic value of at least 3.86 trillion baht. Also found SMEs not more than 5% successful. The rest will be abolished eventually. In order for SMES to be the backbone of their business and the Thai economy, they can stand in the current economic downturn. Entrepreneurs need to adapt their marketing management to maintain their business.

From the management problem of SMEs business mentioned above. Combined with advanced communication technology and Thailand is a country that focuses on agriculture. The problem with most of the product is the product is completely rotten. This type of business is faced with the problem of high agricultural commodity spoilage. Damage or spoilage may be caused by the process of production or may be when shipping. When damaged or rotten, it has a negative impact on revenue and also affected he reliability.

So researchers are interested to address this issue. The objective in this research is to study of the decision support system for customer demand forecasting and inventory management of perishable goods. This research has been modeled and developed as software to support the trading of products. This model can increase revenue and efficient inventory management, which is enough to meet the needs of customers.

From this point, this paper is divided into four main sections which one as follows. Theories and related researches are shown in first section. Secondly, the decision support system for customer demand forecasting and inventory management of perishable goods is descripted and then the results of the decision support system for customer demand forecasting and inventory management of perishable goods are present. Lastly, the conclusion of this research is shown.

II. Theories and Related Researches

Theories and related researches are shown in this section. The principle of the decision support system for customer demand forecasting and inventory management of perishable goods is an algorithm of the decision to the number of orders placed in the store day-to-day. This algorithm can reduce the cost of ordering more than

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necessary. It is also important to manage the warehouse efficiently.

A. Time Series Forecasting Technique

The time series data is data that is recorded or collected over a period of time, such as hour, day, week, month or year [2]. The reason for using time series data is its predictive data. The data has been collected from the past to the present. Let us know the pattern or behavior of the data. The assumption is that. Data to be predicted in the future then it has the same pattern or behavior as the past. For customer demand forecasting techniques in this research, the researchers have selected three techniques for comparing about the accuracy of the ordering forecast is close to the actual value.

B. The Single Exponential Smoothing

The single exponential smoothing is an equation of time series technique. There is using weighted averages in this equation by smooth adjustment coefficient (α)[3]. This algorithm places the most importance of the most recent data, and therefore considers the latest time data, and therefore considers the data time away in sequence that this algorithm is presented in (1).

$$F_{t+1} = \alpha X_t + (1-\alpha) F_t, \quad \text{when } \alpha = 1/N \tag{1}$$

Considering the va3alue of α in (1), it is found that $\alpha = 1/N$ when $N->1$ will result in $\alpha = 1$. If $N->\infty$ and $\alpha->0$ then $0 \le \alpha \le 1$. The optimal forecast we can do is gradually change the alpha value from 0 to 1. The optimal equation gives the lowest of mean squared error (MSE) or mean absolute percentage error (MAPE) and predicts the change in curvature.

C. The Adaptive-Response-Rate Single Exponential Smoothing

The adaptive response rate is an alpha (α) value that can be adjusted automatically when the data format changes. This algorithm can be automatically adjusted from the single exponential smoothing [4]. The forecasting equations are presented in (2)-(5).

$$F_t = \alpha_{t-1} X_{t-1} + (1-\alpha_{t-1}) F_{t-1} \ ; \ t = 2(1)n \tag{2}$$

By

$$\alpha_t = \left| \frac{E_{t-1}}{M_{t-1}} \right| \quad ; \ t = 2(1)n \tag{3}$$

$$E_t = \beta e_t + (1-\beta) E_{t-1} \quad ; \ t = 2(1)n \quad \text{when } e_t = X_t - F_t \tag{4}$$

$$M_t = \beta |e_t| + (1-\beta) M_{t-1} \quad ; \ t = 2(1)n \quad \text{when } e_t = X_t - F_t \tag{5}$$

Let E_t is smoothed error and M_t is absolute smoothed error. α_t value will be changed by β value because E_t and M_t are functions of β . However, α_t value will be changed automatically but the forecasting will depend on the defining of β value. We can adjust this value from 0 to 1 that we change this value incrementally. All time, we define β value then we calculate to find a $F_{t+1}; t = 1(1)n$ value and MAPE value. However, we will select least MAPE value. .

D. The Holt's Two-Parameter Linear Exponential Smoothing

This algorithm is a way to adjust the data according to the method of adjusting the exponential algorithm. Two parameters are used: α and γ . By α is the weight of x in the past and we sum this value with x in the future [4-5]. γ is the rate of trend adjustment. These forecasting equations are shown in (6)-(8).

$$F_{t+m} = S_t + b_t m \tag{6}$$

By

$$S_t = \alpha X_t + (1-\alpha)(S'_{t-1} + b_{t-1}) \tag{7}$$

$$B_t = \gamma (S_t - S_{t-1}) + (1-\gamma) b_{t-1} \tag{8}$$

Let $0 \le \alpha \le 1$ and $0 \le \gamma \le 1$. We try to select α and γ value for making forecasting value, which is most accurate. The method is to find the value of α and let (6) can be predicted accurately. b_t is the smooth adjustment trend and S_t is the smoot adjustment data of γ . The default values of S_t and b_t are $S_t = b_t$ and $b_1 = \frac{X_2 - X_1}{2} + \frac{X_4 - X_3}{2}$.

The Holt's two-parameter linear exponential smoothing is highly flexible. This algorithm cab adapt the trend (b_1) value with the nature of the data changes.

E. The Mean Squared Error (MSE)

The mean squared error equation is used to calculate the forecast error value [6]. This equation is shown in (9).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (X_i - F_i)^2 \ ; \quad MSE \ge 0 \tag{9}$$

Let X_i is the real value and F is the forecasting value..

F. The Mean Abolute Percentage Error (MAPE)

The MAPE is a method for measuring the accuracy of forecasts [7]. This research compare measuring the accuracy of forecasts between MSE and MAPE because we can not tell that how to measure accuracy between MSE and MAPE. Which is better. This equation is shown in (10).

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{X_i - F_i}{X_i} \right| * 100 \tag{10}$$

By $PE_i = \frac{X_i - F_i}{X_i} * 100$ which comes from the kidneys.

Let X_i is the real value and F is the forecasting value.

G. Related Researches

This section presents comprehensive overview of different proposals for the decision support system for customer demand forecasting and inventory management of perishable goods. Paul W. Murray and et al. in 2015[8] presented a method for transposing a high number of individual customers into a small number of clusters of customers with similar demand behavior. The overcome in this research builds a manageable number of forecast models and apply them within each customer segment. J. Huber and et al. in 2017 [9] investigated the applicability of article clustering and hierarchical forecasting as part of a decision support system that enhances the ordering process in order to increase the service level. This research proposed system addresses by providing demand forecasts for all articles at store level and regional level. The ARIMA model was used to apply the method of this research. Widely used nonlinear methods for water demand predict modelling include: nonlinear regression models, bilinear models, threshold autoregressive models, ANN-based models, fuzzy logic, Kalman filter and genetic programming, and decision tree models [10-14]. In addition, statistical forecasting techniques are typically used when historical data are available. Time series forecasting methods find patterns in historical data to predict the future. The time series methods such as moving average and simplex exponential soothing (SES) are often made in practice. SES is also largely used for inventory control system forecasting [15]. Merzifonluoglu studied accelerated product lifecycles and unpredictable customer demand, forecasting remains challenging [16]. Data analytics and human judgment need to be combined to achieve better results, rather than being seen as a dichotomy [17].

III. Research Methodology

The research methodology of study of the decision support system for customer demand forecasting and inventory management of perishable goods consists of the following steps.

A. To Learn Company Information

This step considers such as 1) the sample company information, 2) procedures of working and 3) the problem of warehouse management.

B. To Record the Most Order Goods

We record the most top five of order goods that we store 350 days for order quantity. This research uses a large pork cutlet shop from Bungkan province, which is in Northeast of Thailand. This shop sells more than 300,000 baht per day and sells non-holiday sales. There are available both wholesale and retail.

C. Data Analysis

Three algorithms are used for data analysis in this research. The three forecasts will be compared at this stage. The algorithms used for planning warehouse purchase are the single exponential smoothing algorithm, the adaptive-response-rate single exponential smoothing algorithm and the Holt's two-parameter linear exponential smoothing algorithm. In addition, the methods for evaluating these algorithms are MSE method and MAPE method. However, if MSE value and MAPE value of an algorithm is least from three algorithms then this algorithm is selected to create the decision support system for customer demand forecasting and inventory management of perishable goods.

D. To Apply and to Evaluate the Model

To apply and to evaluate the model are done in this step. This research evaluates this model by looking at the reduced cost of purchasing all five goods into the warehouse.

In addition, all four steps of the research methodology are presented in Fig. 1.

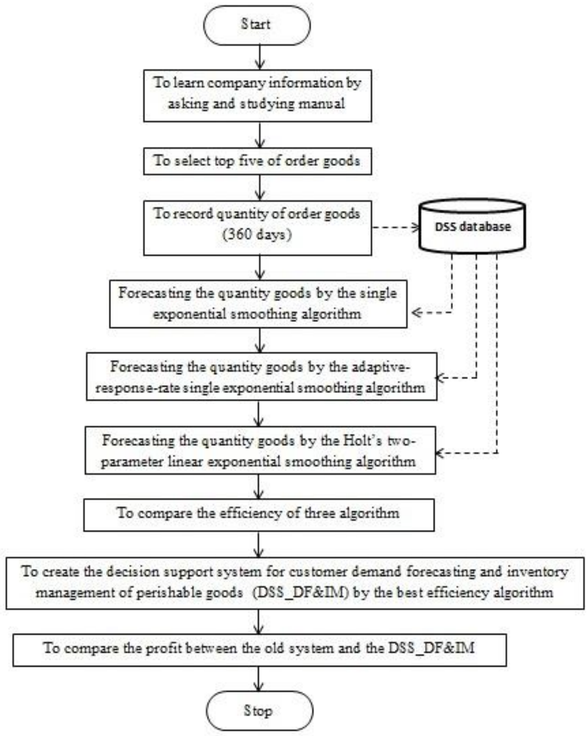

Figure 1. All procedures of research methodology

From Fig. 1, there are many procedures of research methodology. Many algorithms are used forecasting the quantity goods by using equations between (1) and (8). After that, this research compares the efficiency from three algorithms by MSE method and MAPE method, which use (9) and (10). The best efficiency of algorithm is selected and is used to create the decision support system for customer demand forecasting and inventory management of perishable goods (DSS_DF&IM). The last, we compare the between the profit of old system and the profit of DSS_DF&IM.

IV The Results of DSS_DF&IM Model

This section presents the results from studying three algorithms and the development of DSS_DF&IM. A case study of this research is a large pork chop at Bungkan province from Thailand.

A. The Results of the Study of Pork Chop Information

This pork chop sales all pork cuttings not less than 2,000 kg. per day. The problem of this pork chop is inefficient to place orders into the warehouse. Some days the product is not enough to sell. Some days the goods in the warehouse are more than the requirements of the customer. However, According to the survey, the top five selling pork sales were streaky pork, pork ribs, pork hips, pork chop and pork neck.

B. The Results of Sales Volume Record

After studying the information of this pork chop, we can know the top five of selling pork chops. Then the sales volumes of top five are recorded that we present some data in Table 1.

TABLE I. THE SALE VOLUMES OF TOP FIVE OF PORK CHOPS

Date	The sale volumes (kg.)				
	streaky pork	pork ribs	pork hips	pork chop	pork neck
1/4/2016	540	355	355	240	290
2/4/2016	537	320	360	245	300
3/4/2016	492	350	365	245	285
4/4/2016	517	330	340	250	270
5/4/2016	485	325	348	237	267
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
11/3/2017	460	310	350	245	285
12/3/2017	485	300	350	238	280
13/3/2017	472	345	360	235	284
14/3/2017	490	350	347	230	285
15/3/2017	510	325	340	245	280
16/3/2017	515	310	320	250	285
17/3/2017	490	330	335	240	290

C. The Results of Data Analysis

To studying for customer demand forecasting and inventory management of Perishable Goods is focus on balance of goods. If customer demand planning is efficiency then the inventory will also be efficient. In addition, this situation can help to decrease cost for inventory too.

The results of data forecasting from the top five of pork chops by using of the single exponential smoothing algorithm, the adaptive response-rate single exponential smoothing algorithm and the Holt's two-parameter linear exponential smoothing algorithm found that the single exponential smoothing can give lowest mean square error value in every items. All values of mean square error are shown in Table II.

TABLE II. MEAN SQUARE ERROR VALUES OF TOP FIVE OF PORK CHOPS

Date	Mean squared error (MSE)		
	Single exponential smoothing	Adaptive-response-rate single exponential	Holt's two-parameter linear exponential
streaky pork	512.35	515.62	552.27
pork ribs	357.42	364.47	380.54
pork hips	354.74	362.28	396.68
pork chop	258.46	264.38	292.54
pork neck	295.46	305.35	322.32

Table II shows mean square error values (MSE) of top five of pork chop volumes between 1st April 2016 and 17th March 2017.

The single exponential smoothing algorithm is selected to use for developing DSS_DF&IM model. This pork chop order top five goods that they buy top five of pork chops equal the number at Table 2. There is using this model at 25th March 2017. In addition, we present to compare between the profit of the old system and the profit of DSS_DF&IM model that the results are presented in Table 3.

TABLE III. COMPARISON OF PROFIT BETWEEN OLD SYSTEM AND DSS_DF&IM MODEL

goods	Purchase order entry (kg.)		Order quantity (kg.)		Demand quantity (kg.)		Inventory (kg.)		Profit (Baht)	
	old sys.	DSS_DF&IM	old sys.	DSS_DF&IM	old sys.	DSS_DF&IM	old sys.	DSS_DF&IM	old sys.	DSS_DF&IM
streaky pork	550	513	520	513	520	513	30	0	34,000	35,910
pork ribs	450	358	370	350	370	350	80	8	19,500	23,860
pork hips	370	355	310	355	310	360	60	0	16,900	24,850
pork chop	300	259	245	254	245	254	55	5	12,750	17,380
pork neck	300	296	272	280	272	280	28	16	16,800	18,320

Table III presents to compare the profits of the old system and the DSS_DF&IM model. This pork chop purchases pork in each day. For example, streaky pork is purchased for entry the inventory by 550 kg. by the old system. But the DSS_DF&IM model purchased streaky pork is equal 513. In addition, customers bought streaky pork is equal 520 kg. in the old system while customers bought streaky pork is equal 513 kg. in the DSS_DF&IM model. However, the old system did not sell in any goods. For example, streaky port had 30 kg. in the inventory while the DSS_DF&IM model had not streaky port. In addition, the DSS_DF&IM model can make profit more than the old system in any goods that the DSS_DF&IM model is equal 120,320 Baht while the old system is equal 99,950 Baht. Furthermore, outstanding products of the old system are higher than the DSS_DF&IM model in any groups.

V. Conclusions

To study of the decision support system for customer demand forecasting and inventory management of perishable goods is been the objective of this research. The single exponential smoothing algorithm, the adaptive-response-rate single exponential smoothing algorithm, and the Holt's two-parameter linear exponential smoothing are compared the efficiency before to create the DSS_DF&IM model. The top five goods (streaky pork, pork ribs, pork hips, pork chop, and pork neck) of order quantity are used to test in this research. However, the results of comparing these algorithms are shown that the single exponential smoothing is highest efficiency then this model is selected to use in the DSS_DF&IM model. This research compares the efficiency between the old system and the DSS_DF&IM model. The experimental results found that the DSS_DF&IM model can give the profit more than the old system that is equal 20,370 Baht. In addition, all goods of the old system not sold higher than the DSS_DF&IM model that the old system have goods not sold equal 253 kg. while the DSS_DF&IM mode is equal 29 kg.

To find a technique for solving problem the volume of purchases is greater than in the past is been the future research.

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References

[1] R. Sreedevi, and H. Saranga, "Uncertainty and supply chain risk: the moderating role of supply chain flexibility in risk mitigation," *ELSEVIER Trans. on International journal of production economics*, vol. 193, pp. 332-342, Nov. 2017.

[2] Y. Syu, J.Y. Kuo, and Y.Y. Fanjiang, "Time series forecasting for dynamic quality of web services: an empirical study," *ELSEVIER trans. on The journal of systems and software*, vol. 134, pp. 279-303, Dec. 2017.

[3] R.R. Yager, "Exponential smoothing with credibility weighted observations," *ELSEVIER Trans. on Information Sciences*, vol. 252, pp. 96-105, Dec. 2013.

[4] A. Nazim, and A. Afthanorhan, "A comparison between single exponential smoothing (SES), double exponential smoothing (DES), holt's (brown) and adaptive response rate exponential smoothing (ARRES) techniques in forecasting Malaysia population," SPC trans. on Global journal of mathematical analysis, vol. 2, no. 4, pp. 276-280, 2014.

[5] H.V. Ravinder, "Determining the optimal values of exponential smoothing constants – Does solver really work?," *CC-BY trans. on American journal of business education*, vol.9, no. 1, pp. 347-359, Jun. 2013.

[6] C.H. Park, and J.H. Chang, "Shrinkage estimation-based source localization with minimum mean squared error criterion and minimum bias criterion," *ELSEVIER trans. on Digital signal processing*, vol. 29, pp. 100-16, Jun. 2014.

[7] S. Kim, and H. Kim, "A new metric of absolute percentage error for intermittent demand forecasts," *ELSEVIER trans. on International journal of forecasting*, vol. 32, pp. 669-679, Jul.-Sep. 2016.

[8] W. Paul, B. Agard, and M. A. Barajas, "Forecasting supply chain demand by clustering customers," *ELSEVIER Trans. on IFAC papers online*, vol. 48, no, 3 pp. 1834-1839, 2015.

[9] J. Huber, A. Gossmann, and H. Stuckenschmidt, "Cluster-based hierarchical demand forecasting for perishable goods," *ELSEVIER Trans. On Expert systems with applications*, vol. 76 pp. 140-151, Jun. 2017.

[10] M. Tiwari, and J. Adamowski, "Medium term urban water demand forecasting with limited data using an ensemble waveletbootstrap machine-learning approach," *ASCE Trans. on Water resources planning and management*, vol. 141, no. 2 pp. 1-12, 2015.

[11] J. Adamowski, H.F. Chan, S.O. Prasher, B. Ozga-Zielinski, and A. Sliusarieva, "Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada," *AN AGU Trans. on Water resources research*, vol. 48, no. 1, Jan. 2012.

[12] A. Jain, A. Varshney, and U. Joshi, "Short-term water demand forecast modeling at IIT Kanpur using artificial neural networks," Kluwer academic publishers Trans. on Water resources management, vol. 15 pp. 299-321, 2001.

[13] C. Bunett, R.A. Stewart, and C.D Beal, "ANN-based residential water end-use demand forecasting model," *ELSEVIER Trans. on Expert systems with applications, vol. 40, no. 4 pp. 1014-1023, Mar. 2013.*

[14] M. Nasseri, A. Moeini, and M. Tabesh, "Forecasting monthly urban water demand using extended Kalman filter and genetic programming," *ELSEVIER Trans. on Expert systems with applications, vol. 38, no. 6 pp. 7387-7395, Jun. 2011.*

[15] A.A. Syntetos, J.E. Boylan, and S.M. Disney, "Forecasting for inventory planning: a 50 year review," *Springer link Trans. on the operational research society*, vol. 60, no, 1 pp.149-160, May. 2009.

[16] Y. Merzifonluoglu, "Risk averse supply portfolio selection with supply, demand and spot market volatility," *ELSEVIER Trans. on Omega*, vol. 57 pp.40-53, Dec. 2015.

[17] S. Ransbotham, D. Kiron, and P. Prentice, "Beyond the Hype: the hard work behind analytics success," SAS trans. on Mit sloan management review, Mar. 2016.

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