Enhancing the Forecasting Performance with the Hybrid Machine Learning Techniques for Online Shopping Channels: A Case Study of Electronic Products in Thailand

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Abstract— This study proposes novel hybrid forecasting models, which are the combination between Long-Short Term Memory (LSTM) recurrent neural network and traditional models. The objective is to investigate the trend of customer behavior on electronic products and reduce the demand variation that will be impact the total cost in the supply chain. In order to prove the performance of our proposed hybrid models, a Thai company case study is tested with four online shopping electronic products. Accuracy and demand variation are used to compare the effectiveness of our hybrid forecasting model. For the accuracy, some performance indicator tools, such as MAE, RMSE, and MASE, show that the hybrid models provide the lowest error among these indicators with three products, while the single LSTM provide the lowest error with only one product. For the demand variation, all forecasted demand provide the coefficient variation (CV) score less than 0.25, which mean that all products are less variation, and can be used to calculate the forecast stock levels in the company.

Keywords— Hybrid forecasting, LSTM, Machine learning, Electronic product.

I. Introduction

Recently, the trend of E-commerce is widely growing up after the Covid-19 pandemic since year 2020. It can be seen that, in Thailand, the growth rate of E-commerce was augmented approximately 11 billion USD in year 2020 and probably increase to 52 billion USD within five years [1]. The average growth rate is around 35% per year. Moreover, the Omnichannel is more popular than the past regarding the changing of customer behaviors in the market and the pandemic. We can see that more than 82% of Thai customers buy their products in both offline and online shopping channels [2]. Moreover, the customer demand for shopping via online channels is drastically increasing due to Covid-19 during these three years. In fact, the Covid-19 pandemic is not only impacting the buying behavior, but it also affects the lifestyle of customers. The pandemic is coming in parallel with the "Internet of Things" from year 2020 until now. It means that many people prefer working and doing business from home nowadays.

Regarding the following reason, the consumption rate of electronic products is more growing up than the past. In Thailand, the electronic product sales were increasing drastically in year 2021 and the market value was enriched approximately 9.5% after comparing in year 2020 [3]. The trend of buying electronic products still continuously expands nowadays. Even though, the sales of electronic products are higher and best sellers in some periods. The company still faces some problems from the customer behavior in these products.

- Firstly, the customer demands are fluctuated in some periods, for example, the demand for electronic products are increasing at the beginning of the year and rapidly decreasing at the end of the year.
- Secondly, regarding the demand fluctuation in the first problem, this phenomena will impact the product stock levels for online channels. The stock levels can be exceeds or unsatisfied customer demands.

Using forecasting techniques are very powerful to reduce the demand fluctuations both stock planning and the overall performance of the whole supply chain[4]. Thus, we are interesting to investigate and forecast the trend of customer behavior on electronic products using different forecasting techniques. Different forecasting techniques have been explored in the literature [5]. In this study, we first begin the experiment with using single forecasting techniques, such as Triple Exponential Smoothing (ES3), Support Vector Regression (SVR), and Auto-regressive Integrated Moving Average (ARIMA) and Long-Short Term Memory (LSTM). Then, we propose hybrid forecasting models, which are the combination between these traditional techniques (which are statistic and regression techniques) and a recurrent neural network technique, to discover the applicable model to forecast both linear and non-linear trends. The models have been tested on a Thai company case study with four online shopping electronic products sales data in order to first, identify which forecasting models would be appropriate to forecast the customer demands of electronic product sales. Second, to manage the fluctuation of customer demands and trends in different electronic products.

The rest of the paper is divided into five sections. Section 2 reviews the literature on difference forecasting techniques that have been proposed and tested on the same dataset of electronic products sales of online shopping channel. Section 3 describes more details about the methodology and the implementation of the proposed hybrid forecasting models. Section 4 demonstrates the results of the proposed models and compares the results with some existing forecasts both traditional and RNN models. Section 5 summarizes all perspectives as well as provides an extension for future study.

II. Literature Review

This section has four sub-topics; Customer behavior of online shopping channel, Forecasting techniques, Hyperparameter tuning, and Research gaps. All details are described below.

A. *Customer behavior of online shopping channel*

Omnichannel Marketing is one of the most famous business strategies that are implemented in many organizations nowadays [6], because this strategy can increase the shopping options for customers both offline and online channels. It means that customers have more opportunities to order their products, including electronic products. In additions, most customers recently change their behavior to buy their products via online channels, such as shop websites, shop mobile applications, social medias. Several works focused on the customer behavior of online shopping for electronic products. For instance, the authors [7] investigated which factors impact to the customer shopping experience after applying the modified electronic technology acceptance model (e-TAM) to visualize electronic products. They collect data from online shoppers using the online survey and analyze the results with SEM model. Another work [8] also studied the consumer behavior for electronic online shopping in Bhopal and Jabalpur cities. The results showed that some factors, such as time saving, product quality, product price, and convenience encourage customers to buy electronic products via online channels. These existing studies demonstrate that the customer behavior recently changes the way how they buy electronic products from offline to online channels from time to time.

B. *Forecasting techniques*

This research work will mainly focus on techniques for time-series data regarding the historical data of customer demands from a company case study. Due to the performance of forecasting models in previous studies [4], [9], [10], we are interesting to continually study in traditional and neural network models. Triple Exponential Smoothing (ES3), Support Vector Regression (SVR), and Auto-regressive Integrated Moving Average (ARIMA) are considered as traditional techniques. Then, Long-Short Term Memory

(LSTM) is considered as a recurrent neural network technique. All details of these techniques are described below.

Triple Exponential Smoothing (ES3)

This technique is an extension of Exponential Smoothing that explicitly focuses on three components; Level, Trend, and Seasonal [11], [12]. This method is sometimes called Holt-Winters Exponential Smoothing or Holt's method. Additionally, there are three main parameters that require to indicate: alpha, beta, and gamma. This technique is quite suitable for univariate input factors [12], [13], which are the same input type of our study.

Auto-regressive Integrated Moving Average (ARIMA)

This technique proposes the forecasting solution based on three main components; Autoregressive(p), Differencing Order(d), and Moving Average(Q), and it provides a good forecasting performance both seasonal and non-seasonal demand [14]. In addition, this technique works well with time-series data in a short-period [15].

Support Vector Regression (SVR)

This technique is a part of Support Vector Machine (SVM) and its characteristics is for the regression problem [16]. Moreover, this technique is quite popular to forecast time-series data in difference contexts, such as the future demand in the supply chain [4], [5], [17]. Generally, SVM classifies data using the hyperplanes. SVR still implements the same concept of SVM, but there are still a few differences. SVR prefers to discover the hyperplanes' equation that can minimize error [16]. This technique also responses well performance with univariate data [9].

Long-Short Term Memory (LSTM)

This technique is one of the most suitable techniques in the recurrent neural network group for time-series data [18]. The concept of this technique is to forecast demand via short-term and long-term memory cells [4], [19], [20]. Furthermore, this technique can forecast demand by avoiding the vanishing and exploding gradient descents. It means that the weight in each cell will be updated all the time when the model trains the data in each epoch. Several relevant works are also mentioned in this study. These works focus on forecasting techniques for time-series data. Firstly, the paper [9] proposed an appropriate forecasting model to forecast the trend of white sugar consumption rate in Thailand. Regression and neural network models were considered in the study. The results showed that LSTM provides the best performance after comparing with other models via RMSE and Theil'U scores. Secondly, the authors in [10] studied the performance of forecasting time-series data between the exponential smoothing (ES) and artificial neural network (ANN) models. In addition, the researchers proposed a novel hybrid model, which is the combination of ES and ANN to solve the prediction problem of non-linear with trend and seasonal data. The results showed that the hybrid model can forecast on different data types very well after comparing with single models. Some authors [21] studied the performance of Feed-forward Neural Networks (FFNNs), Auto-regressive Integrated Moving Average (ARIMA), and Exponential Smoothing to forecast the situation of Covid-19 pandemic in Iraq. The results illustrated that FFNNs model provides the higher accuracy of forecast patients than other models. The accuracy is approximately 87.6%.

When we move to study some relevant works about demand forecasting in electronic and related products, we find a few related works in Thailand. For example, the authors [22] has implemented four forecasting techniques; Moving Average, Decomposition, Exponential Smoothing, and ARIMA, to forecast future demands of different consumer products. The results present that 73 products from 173 products are appropriate to forecast using Moving Average, while more than 64 products required to improve the forecasting solution. Another work [23] has studied how to reduce the error in the forecasting sales of electrical products by implementing the data transformation and forecasting techniques for time-series data. The results shows that the triple exponential smoothing (ES3) provides the lowest MAPE score at 2.81 percent with a statistically significant 0.01.

C. *Hyperparameter tuning*

In addition, all proposed techniques require to tune hyperparameter in their model structure. The objective of hyperparameter tuning is to find the optimal solution for the forecasting models. The appropriate hyperparameter configuration will increase the accuracy of the forecast demand. Several popular techniques have been proposed in existing studies. For example, the authors [4] proposed scatter search and genetic algorithms to tune hyperparameter, such as the number of hidden layers, the number of neuron units per layer, activation functions, and optimizers in the LSTM model. The results showed that LSTM recurrent neural network provides highest forecasting performance after comparing with other forecasting models. Another study [24] also proposed the optimization of hyperparameter tunings in a convolutional neural network architecture via grid search, random search, and genetic algorithm. The results demonstrated that grid search and random search are appropriate for hyperparameter tuning with small and medium datasets. However, genetic algorithm is preferable for the large dataset with higher accuracy and faster computational time. Lastly, the research work [25] implemented Akaike Information Criterion (AIC) and GridSearch (GS) to adjust hyperparameters p, d, q in ARIMA and hybrid ARIMA models. The objective is to forecast the volume of PM 2.5 in Beijing. The results showed that hybrid ARIMA provides the high accuracy of forecasting volumes in PM 2.5 around 99%. In this study, the tuning hyperparameter techniques will be implemented for each forecasting technique and provided more details in the methodology.

D. *Research gaps*

Even though, some existing works have been studied and implement the concept of demand forecasting in different contexts, there are still some research gaps that we discover from these works.

- Few studies have implemented the forecasting techniques to reduce the demand variation of the electronic product sales in Thailand that is non-linear data.
- No studies have generated the forecasting model dynamically for different products with different behaviors' sales in Thai electronic product case study.

In our previous paper [4], we already proposed LSTM forecasting model, however, the model was tested on the daily data of agricultural products that was generated through Dirichlet distribution law. Thus, in this paper, we first test our previous LSTM and traditional models on the real dataset of daily electronic product sales from online channels of Thai company case study. Then, we propose two hybrid models. All details will be described in the methodology section.

III. METHODOLOGY

Figure 1 illustrates the flow chart of developing our hybrid forecasting models. All steps are developed using Python programming language via Google Collab. The details of steps are described below.

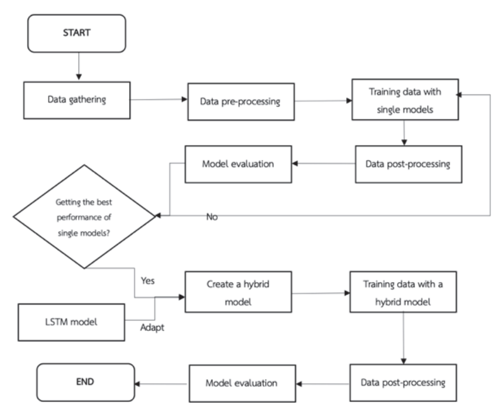

Figure 1. The flowchart of forecasting process improvement.

A. *Data gathering*

In this study, we collect data of the daily demand in four online electronic SKUs. The considered period is from 1 January to 31 December 2022. In addition, the daily demand of all electronic products is from the company case study in Bangkok and metropolis area.

B. *Data pre-processing*

This step consists of Data cleaning and Data transformation. For Data cleaning, we check all mistaken points, such as missing values, and typographical errors, in the dataset. For Data transformation, there are several methods to transform the data before training a model. Data normalization is chosen to transform the data in this study and the method *Standardscalar*, which is the normalization function in Python libraries, will be implemented to transform data.

C. Training data with single models

After finished the data-preprocessing, all datasets will be trained with proposed forecasting techniques. These techniques, which are recurrent neural network and traditional techniques, will be implemented to train data. LSTM is considered for a recurrent neural network technique. Then, traditional techniques, such as ES3, SVR, and ARIMA are chosen for training data. In addition, these forecasting techniques are developed using Python because this programming language has variety of related libraries for developing machine learning algorithms [26]. Furthermore, we will tune hyperparameters, such as number of layers, number of neuron units, activation function, and optimizer using hybrid Genetic Algorithm and Scatter Search [4] for LSTM with Epoch from 100-500 epochs. Also, for other techniques, we tune their hyperparameters as well. For example, ES3 focuses on trend and seasonal parameters, which compose of additive and multiplicative. Also, ARIMA focused on p,o,q order and seasonal p,o,q order parameters. SVR focuses on kernel and maximum iteration parameters.

D. Data post-processing.

After finished training model, all datasets require to do the post-process. The objective is to convert scaling data to original data. Data de-normalization is considered to convert from scaling data to original data in this study.

E. Forecasting Performance Evaluation

There are two indicators to evaluate the forecasting performance: accuracy, and the demand variation. MAE, RMSE and MASE are chosen to evaluate the forecasting accuracy. The single model with lowest scores from these four indicators are considered to be a part of hybrid models. Also, CV (Coefficient Variation) score is considered to evaluate the demand variation [27]. The CV score should be less than 0.25 to be confirm the less variation and the model is appropriate to implement.

F. Develop hybrid forecasting models

After Evaluating the performance of single models, we will choose one of traditional techniques that has the best performance to create hybrid models with a proposed model in the recurrent neural network based on LSTM. The objective is to create a new model that can forecast the future demand with non-linear trend and seasonality based on the product item. Then, we run the same process as shown in the single model, such as Data pre-processing, Training data with hybrid models, Data post-processing, and forecasting evaluation. We also config hyperparameters in proposed hybrid models as well.

IV. RESULTS ANALYSIS AND DISCUSSION

A. Forecasting performance: Single model

This section illustrates the evaluation of forecasting performance between single traditional forecasting models (SM1) and a single LSTM model (SM2). Based on MAE, RMSE, and MASE scores, we can see that SVR provides the best performance with three SKUs from all, while ES3 provides the best performance only SKU_3. However, after comparing performance with the SM2 model, the results show that single LSTM mostly delivers better forecasting performance than SM1 models because of lower error scores with all indicators. All details are presented in Table I. Then, we create hybrid forecasting models based on the results in this section.

TABLE I. THE EVALUATION OF FORECASTING PERFORMANCE BETWEEN SINGLE TRADITIONAL AND LSTM MODELS

Electronic product	SM1 model	Forecasting Performance					
		RMSE		MAE		MASE	
		SM1	SM2	SM1	SM2	SM1	SM2
SKU_1	SVR	8.47	**7.47**	6.31	**5.38**	0.9	**0.77**
SKU_2	SVR	3.64	**3.43**	2.88	**2.72**	0.81	**0.79**
SKU_3	ES3	3.27	**2.77**	2.46	**2.06**	0.93	**0.79**
SKU_4	SVR	2.44	**2.36**	1.75	**1.68**	0.79	**0.76**

B. Forecasting performance: hybrid machine learning model

Regarding results from Table I, we create two hybrid models with the principle of stacking model, and the equation of hybrid model is inspired by [10]. It means that we will train many models at the same time with the same datasets. Then, the result from each model will be transferred to train in the last model with different weights. In this study, we created two hybrid models with different combinations. The first combination is LSTM and SVR (HFM1), and the second combination is LSTM and ES3 (HFM2). In addition, we optimize the alpha value using both GRG nonlinear and the way to calculate the fixed alpha in [10]. The results present that the hybrid models provide lower score of MAE, RMSE, and MASE than traditional models for SKU_1, SKU_3, and SKU_4. However, for SKU_2, the single LSTM provides better performance with lower errors. All details are demonstrated in Table II.

TABLE II. THE EVALUATION OF FORECASTING PERFORMANCE BETWEEN SINGLE LSTM AND HYBRID MODELS

Electronic product	Forecasting Performance					
	RMSE		MAE		MASE	
	SM	HB	SM	HB	SM	HB
SKU_1	7.47	**7.39**	5.38	**5.24**	0.77	**0.76**
SKU_2	**3.43**	3.44	**2.72**	2.73	**0.79**	0.80
SKU_3	2.77	**2.76**	2.06	**2.02**	0.79	**0.77**
SKU_4	2.36	**2.33**	1.68	**1.64**	**0.76**	0.77

SM: ALL SINGLE MODELS BOTH LSTM AND TRADITIONAL MODELS
HB: HYBRID FORECASTING MODEL

Moreover, we calculate the coefficient variation (CV) score of forecast data from all SKUs based on the best performance model. We find that all SKUs provide the CV score lower than 0.25, which means that we can bring the forecast data to plan the inventory levels for electronic products in the company case study. All details are demonstrated in Table III. Depending on the item of product, the performance of HFM is different. For SKU_1 and SKU_4, HFM1 have been choose because it provides better results. However, HFM2 was selected for SKU_3. For SKU_2, single LSTM still provided greater performance than the hybrid model.

TABLE III. THE EVALUATION OF COEFFICIENT VARIATION FOR ALL FORECASTED SKUS

Electronic product	Best forecasting model	CV score
SKU_1	HFM1	0.04
SKU_2	LSTM	0.03
SKU_3	HFM2	0.13
SKU_4	HFM1	0.02

HFM1: HYBRID LSTM-SVR MODEL, HFM2: HYBRID LSTM-ES3 MODEL

V. CONCLUSION

This paper sheds light on how ML increase the performance of forecasting. A hybrid forecasting model-based ML techniques was proposed. Firstly, we prepare and experiment all electronic product sales' datasets with single traditional and LSTM models. We find that LSTM mostly provide better performance with lower error scores. Then, we create hybrid models by combining between the best performance model from traditional models and single LSTM based on the item product. The results show that hybrid models both hybrid LSTM-SVR and hybrid LSTM-ES3 mostly indicate better performance than single models. In addition, the CV score of all forecast products is less than 0.25, which means the company can bring the forecast demands to manage the inventory levels and create the distribution plan in the company. As future work, we aim to test these forecast demands on Physical Internet supply chain network with the inventory levels of PI-hubs and distribution plan.

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