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Enhancing the PI Distribution Network Performance with Hybrid ML Forecasting Techniques Applied to a Case Study of Electronic Products in Thailand

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ABSTRACT

The consumption rate of different products such as electronic devices has drastically increased since the onset of COVID-19 in 2020. This shift in behavior has significantly impacted on the efficiency performance of supply chain in many countries. Using Physical Internet (PI) paradigm as an open global logistics system for increased efficiency and sustainability has been proved in different studies in the literature. Different forecasting models have been developed to predict demand fluctuations that have also been explored. However, in this work, we focus on designing different hybrid forecasting models in a dynamic way based on data analysis. Single and hybrid forecasting models, utilizing traditional and neural network techniques, have been used to design our models. The experimental data is drawn from a real case study of an electronic company in Thailand. These forecast outputs are then used to manage resources within a PI distribution network dynamically. The results indicate that hybrid forecasting models outperform other techniques in predicting the sales of three electronic Stock Keeping Units (SKUs), while only one SKU performs well with a single LSTM model. The appropriate hybrid combination model is dynamically chosen based on the forecasting performance of each SKU item. The forecast results also prove that the distribution distance, time, and cost in the PI distribution network are reduced by approximately 41%, 26%, and 49% for Bangkok and its metropolitan area, and these parameters decrease by around 14%, 11%, and 34% in the Central-Eastern regions.

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1. INTRODUCTION

To improve the supply chain network performance, the Physical Internet (PI) paradigm has been developed. It is an open supply network with a fully connected component [1], [2]. Various studies in the literature have explored the efficiency of solving the distribution problem in the PI network. For instance, the authors [3] proposed the optimization designs for smart locker banks, which are used to contain several products for omnichannel customers in the PI distribution network. The smart locker banks were designed and optimized on both fixed and modular towers. Also, the authors [4] demonstrated that adopting the PI approach enhances the flexibility of goods movement within distribution networks. One more study [5] investigated how the characteristics and design of PI-containers influence container flows within domestic networks. Using a Linear Programming (LP) model, they aimed to minimize flow imbalances between hubs and optimize the compatibility of PI-containers in each truck. Additionally, PI enhances the distribution network, making it more flexible and reliable by creating hyper connections among all parties in the chain compared to classical ones [4], [6].

However, fluctuations in demand decrease the performance of the supply chain. This can lead to disruptions, such as the bullwhip effect, especially in complex distribution networks like PI. One effective solution to mitigate demand fluctuation issues is demand

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forecasting. Thus, various researchers have explored and implemented different forecasting techniques to address this problem. In fact, using such tool has proven to be powerful tool in understanding customer behavior trends and enhancing supply chain performance, leading to cost reduction and minimizing inventory and transportation variations [7].

In the PI network configuration, various forecasting techniques have been examined in existing literature [7], [8]. Results have demonstrated that using forecasting models further improve the efficiency of the PI network, particularly in reducing transportation and holding inventory cost. Even though several forecasting techniques have been implemented to enhance the performance of the PI distribution network, existing studies focus only on a single product. However, many industrial sectors recently produce and distribute multiple products to their customers, including wholesalers, retailers, and individual customers, within a complex network. Moreover, since the COVID-19 pandemic in 2020, industrial sectors has increasingly implemented the Omnichannel Marketing strategy for product distribution [9].

Regarding the fluctuation of customer demand during the pandemic, this phenomenon impacts the consumption rate of several goods, including electronic products, in various regions. In Thailand, for example, the demand for electronic products has significantly increased during the past three years since 2021 due to the convenience and flexibility [10]. This situation is not limited to Thailand. It also happened in several countries around the world. Nevertheless, despite the notable growth in electronic devices demand during certain periods, companies continue to face challenges in understanding customer behavior in relation to electronic products.

- Firstly, customer demand has fluctuated in certain periods. For instance, electronic shipments increased at the beginning of the period, but demand drastically decreased in the last two quarters [11]. Another example is the volume of certain household products, which initially decreased in the first two months, but then sharply increased in the following three months [12].
- Secondly, the stock levels for online channels may lead to overestimations or unsatisfied customers due to the demand fluctuations mentioned in the first issue. This situation will affect the total cost of the PI distribution network.
- Lastly, with the recent surge in online shopping, the company is facing significantly higher distribution costs for the classical distribution network between online customers and the warehouse. Typically, all online orders are distributed to each customer individually, even if some customers are located in the same area or village.

Based on the background and problem statements presented, this study aims to explore different forecasting algorithms to develop corresponding hybrid forecasting models for the multiple products PI distribution problem. The optimal combination between Machine Learning (ML) and traditional techniques will be dynamically selected based on the dataset used. In this study, we utilize actual demand of electronic sales. The objective is to design and determine suitable hybrid models for forecasting customer demands. These hybrid model forecasts will be compared with baseline models, including traditional statistic models, and single Long-Short Term Memory (LSTM) as outlined in prior research [13]. Moreover, the forecast results of the hybrid forecasting models mentioned above will be tested on the PI distribution network configuration. The simulation model is proposed to design the PI distribution network, enabling the testing of both forecasted and actual demands. The configuration of the PI distribution network will be designed based on the forecasted demand. Distribution cost, distribution time, and carbon emission will be used as Key performance Indicators (KPIs) to compare the results. Additionally, we also compare the results with the classical distribution network.

The rest of the paper is divided into five sections. Section 2 reviews the literature on difference forecasting techniques both single and hybrid forecasting techniques using in the supply chain network, including PI. Also, some relevant existing studies are indicated in this section. Section 3 describes more details about the methodology and the implementation of the proposed hybrid forecasting models and PI distribution network. Section 4 illustrates the results of the proposed hybrid models and compares the results with baseline models. Furthermore, the results of PI distributions, which are compared with the Classical distribution, are displayed in this section. Section 5 summarizes all perspectives and provides suggestions for future study.

2. LITERATURE REVIEW

The literature review is structured as follows. Firstly, relevant forecasting techniques used in the PI network are introduced, highlighting their advantages and formulations. Secondly, several hybrid forecasting models used in the supply chain network are proposed. Thirdly, existing studies of hyperparameter tuning are examined, with a focus on demonstrating the critical role of hyperparameter tuning in enhancing forecasting performance. Finally, the research gaps of the demand forecasting in the PI distribution problem are discussed. Additionally, we will show how integrating these two aspects addresses the identified gap.

2.1 Forecasting techniques used in the PI network

Several existing studies implemented baseline forecasting techniques to enhance the performance of PI networks in different contexts, such as forecast demand for inventory levels and transportation planning [7], [14], and forecast PI-hub inbound containers [15]. The baseline techniques from these studies are Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), Triple Exponential Smoothing (ES3), and Long-Short Term Memory (LSTM). The details of these techniques are described below.

2.1.1 Autoregressive Integrated Moving Average (ARIMA)

This technique generates the forecast demand with the combination of Autoregressive (AR), Moving Average (MA), and differencing operators (D). It performs well with trend, seasonal, and non-seasonal demands [16]. Moreover, the proposed $ARIMA(p, d, q)$ refers to a model with p (AR) terms, q (MA) terms, and d (D) terms. This model is one of the most implemented models to forecast time-series demands in the supply chain context [17], [18]. The details of the ARIMA structure modified from [17] are shown in Equations 1 – 3.

$$\varphi_p(L)(1-L)^d F_t = \theta_q(L)\,\varepsilon_t \quad (1)$$

$$\varphi_p(L) = 1 - \sum\nolimits_{i=1}^{p} \varphi_i L^i \quad (2)$$

$$\theta_q(L) = 1 - \sum\nolimits_{i=1}^{q} \theta_i L^i \quad (3)$$

Subject to:
F_t = forecast data at time t
$\varphi_p(L)$ = the AR term
$\theta_q(L)$ = the MA term
(L) = the lag operator
$(1-L)^d$ = the differencing operator

2.1.2 Support Vector Regression (SVR)

This technique is a sub-model within the Support Vector Machine (SVM) technique. It is specifically proposed for addressing forecasting regression for small problems [19]. This technique is widely used for forecasting time-series data in several supply chain activities [8], [20], [21], including in the PI context [7], [15], [22]. SVR classifies data using hyperplanes, similar to the Support Vector Classification (SVC) model. However, SVR determines the hyperplane equations that provide lowest noises [19], [23]. The structure details of the SVR linear model and risk minimization are shown in Equations 4 - 5.

$$F = x * X + b \quad (4)$$

$$Z = \frac{1}{2} * (w)^2 + C * \sum\nolimits_{i=1} (\xi_i + \xi_i^*); \xi_i, \xi_i^* \geq 0 \quad (5)$$

Subject to:
F = forecast data
X = input factors
w = weight of factors
b = bias parameter
Z = the risk minimization score
ξ_i, ξ_i^* = loss function
C = regression error penalty factor

2.1.3 Triple Exponential Smoothing (ES3)

This technique is part of the exponential smoothing techniques. However, the model structure differs from other ES techniques. ES3 focuses on three components: level, trend, and seasonal [24], [25]. This method is also known as the Holt-Winters Exponential Smoothing method. Furthermore, three main parameters are required: alpha (α), beta (β), and gamma (γ). This technique is particularly suitable for univariate input factors [25], [26], which is the same input type as our study. Additionally, the level and seasonal components can be combined additively or multiplicatively. The details of the ES3 structure [27] are shown in Equations 6 – 13.

Additive combination:

$$L_t = \alpha(Y_t - S_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1});\ 0 \leq \alpha \leq 1 \quad (6)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1};\ 0 \leq \beta \leq 1 \quad (7)$$

$$S_t = \gamma(Y_t - L_{t-1} - T_{t-1}) + (1-\gamma)S_{t-p};\ 0 \leq \gamma \leq 1 \quad (8)$$

$$F_{t+n} = L_t + nT_t + S_{t-p+n} \quad (9)$$

Multiplicative combination:

$$L_t = \alpha\left(\frac{Y_t}{S_{t-p}}\right) + (1-\alpha)(L_{t-1} + T_{t-1});\ 0 \leq \alpha \leq 1 \quad (10)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1};\ 0 \leq \beta \leq 1 \quad (11)$$

$$S_t = \gamma\left(\frac{Y_t}{L_{t-1} + T_{t-1}}\right) + (1-\gamma)S_{t-p};\ 0 \leq \gamma \leq 1 \quad (12)$$

$$F_{t+n} = (L_t + nT_t)S_{t-p+n} \quad (13)$$

Subject to:
L_t = Level at time t
T_t = Trend at time t
S_t = Seasonal at time t
F_{t+n} = forecast data at time $t+n$
p = considered period length
n = forecast step
S_{t-p+n} = estimated seasonal

2.1.4 Long-Short Term Memory (LSTM)

One of the most effective techniques in the Recurrent Neural Network (RNN) group for forecasting time-series data is Long-Short Term Memory (LSTM) [28], [29]. The forecasting concept of this technique is based on short-term and long-term memory cells [7], [30]. This technique was developed to address the vanishing and exploding gradient descent problems. During each training round, the weight in LSTM cells will be adjusted. This mechanism reduces noise and improves the forecast accuracy, bringing the forecasted data closer to the actual data. The details of the LSTM structure are shown below.

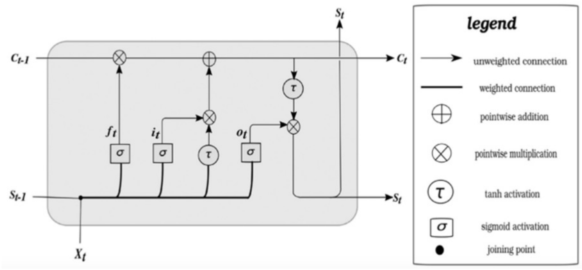

Fig. 1: *The structure of the LSTM cell [29].*

In Figure 1: X_t is the input at time t and represents the external factors; The operator $\oplus$ is the pointwise addition; The operator $\otimes$ is the matrix product term to term; The sigmoid function and the hyperbolic tangent function are represented by σ and τ symbols. In addition, other activation functions can be implemented in the cell. There are five forecasting steps for each LSTM cell. Firstly, the forget gate (f_t) decides which information must be removed from the cell. Secondly, the incoming data for the LSTM cell state will be chosen at the input gate (i_t). Thirdly, the existing cell state (C_{t-1}) value is improved to the new state (C_t). Then, the output gate (o_t) screens which information should be produced as output. Lastly, the value of the hidden state (S_t) is constructed. LSTM equations are described in more detail in the following paper [29].

Several studies have integrated demand forecasting with PI distribution networks. Firstly, the authors [31], [32] introduced a dynamic pricing model that forecasts the volume of transport requests for upcoming auction periods at destination hubs. The objective was to enhance total profit and revenue from transportation rounds, addressing constraints such as Less-than-truckload shipments. Secondly, the authors [7] demonstrated that the LSTM model with hyperparameter tuning using hybrid GA-Scatter Search was outperformed than other forecasting techniques. The datasets of agricultural products were examined for the forecasting performance in all techniques. One more work [14] proposed a Vehicle Routing Problem with Simultaneous Pick-up and Delivery (VRPSPD) within the PI distribution network to optimize transportation and holding costs for agricultural products. This study utilized forecasted demand as input.

Although several single forecasting techniques provide good performance in the PI network, such as demand fluctuation reduction, they cannot cover all behaviour patterns and trends in reality. To enhance forecasting performance, the combination of ML and traditional forecasting techniques must be investigated. Regarding the existing reviews, there is no information about the implementation of hybrid forecasting models in the PI context. Therefore, in the next section, we present the concept of hybrid forecasting models used in the supply chain network.

2.2 Hybrid Forecasting models used in the supply chain network

In this study, all hybrid forecasting models will focus on the combination of LSTM and traditional models regarding the results in a prior study [13]. Some prevailing studies have proposed combinations of neural network and baseline models.

Firstly, the authors [33] proposed a hybrid LSTM-ARIMAX model to forecast the housing sales in Turkey based on historical data spanning 124 months. The study considered price as an exogenous variable in the model and adjusted the model's weight based on the obtained error. Secondly, the work [34] developed the hybrid LSTM-SVR model to forecast abnormal passenger flow at an urban rail transit station in Guangzhou, China. The study evaluated the forecasting performance using MAPE, RMSE, and MAE scores, revealing that the hybrid LSTM-SVR provides higher accuracy than single traditional models such as SVR, LSTM, ARIMA, and Fusion-KNN. The authors [35] studied the performance of forecasting time-series data between the Exponential Smoothing (ES) and Artificial Neural Network (ANN) models. They proposed a novel hybrid model combining ES and ANN to address the prediction problem of nonlinearity with trend and seasonal data. The results showed that the hybrid model can forecast various data types very well when compared with single models. Additionally, two other studies are quite similar to [35]. The authors [23] also implemented the combination of LSTM-SVR to model traffic patterns and generate forecast data of traffic speed. The experiments demonstrated that the prediction performance outperforms other baseline models such as ARIMA, SVR, LSTM, and Historical Average (HA). Lastly, the author [19] proposed integrating an LSTM-SVR model to forecast structural damage trends in buildings. The results showed that the integrated LSTM-SVR model provides lower MAPE, RMSE, and SDAPE scores than the single LSTM and SVR models, indicating greater accuracy and stability.

Regarding the list of forecasting combinations between neural network and traditional models, most combination models are based on LSTM-Traditional models, such as SVR and ARIMA. Next, we provide more details about the structure of the combination of LSTM and these traditional models.

2.2.1 LSTM-SVR model

Most previous studies focused on the combination of results between LSTM and SVR models. Firstly, each model is trained, and the forecasting results are generated individually. Secondly, the results from these two models are concatenated and used to recalculate the second forecasts based on the weights of these models. The hybrid LSTM-SVR model flowchart and equation are shown in Figure 2 and Equation 14. Equation 14 is modified from [19], [34].

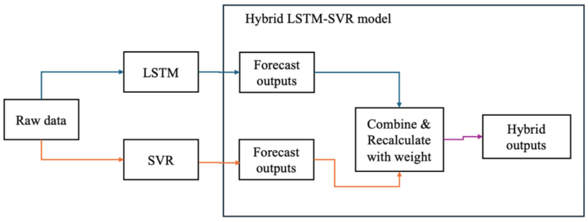

Fig.2: *The hybrid LSTM-SVR model flowchart, modified from [19], [23].*

$$Y_t = \alpha * Y_{LSTM[t]} + (1-\alpha) * Y_{SVR[t]};\ 0 \le \alpha \le 1 \quad (14)$$

Subject to:

Y_t = forecast output at period t
$Y_{LSTM[t]}$ = LSTM forecast output at period t
$Y_{SVR[t]}$ = SVR forecast output at period t
α = coefficient value or impact weight

2.2.2 LSTM-ARIMA model

Another study discussed the integration of results between LSTM and ARIMA models. The LSTM model is trained, producing forecast errors and weights. Meanwhile, the ARIMA model generates forecast outputs and weights after completing its training. Subsequently, the results from these models are combined and used to recalculate the forecast outputs based on the proposed equations. The hybrid LSTM-ARIMA model flowchart and equation are shown in Figure 3 and Equations 15-19. Equations 15-19 are modified from [33].

$$Y_t = ((W_{LSTM} * E_{LSTM}) + (W_{ARIMA} * Y_{ARIMA[t]}))/2 \quad (15)$$

$$W_{LSTM} = \left(1 - \left(\frac{E_{LSTM}}{E_{LSTM} - E_{ARIMA}}\right)\right) * 2 \quad (16)$$

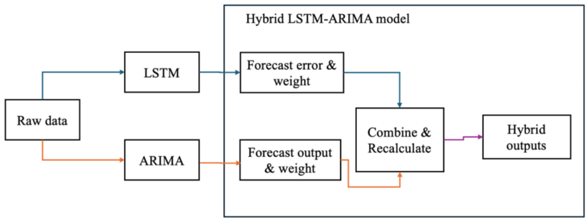

Fig.3: *The hybrid LSTM-ARIMA model flowchart, modified from [33].*

$$W_{ARIMA} = 2 - W_{LSTM} \quad (17)$$
$$E_{LSTM} = LSTM\_Mean\_error \quad (18)$$
$$E_{ARIMA} = ARIMA\_Mean\_error \quad (19)$$

Subject to:

Y_t = forecast output at period t
$Y_{ARIMA[t]}$ = ARIMA forecast output at period t
W_{LSTM} = LSTM model weight
W_{ARIMA} = ARIMA model weight
E_{LSTM} = LSTM model error
E_{ARIMA} = ARIMA model error

Existing studies have demonstrated that combining neural networks with traditional models yields better performance than using either single neural networks or regression models alone. Even though, the proposed hybrid models in existing studies are outperformed than single forecasting techniques, they are generally implemented to forecast demand in the classical supply chain network. Few works have addressed hybrid forecasting models in the PI distribution of multiple products. Moreover, based on the three combination forecasting models above, we can see that the traditional model used in each model is static. When we delve into the specifics of these hybrid models, it becomes evident that one of the most impactful factors enhancing forecasting performance is hyperparameter tuning. However, the hyperparameter tuning used in each existing model is fixed to a single solution. In the following section, we will provide a detailed explanation of hyperparameter tuning and discuss relevant studies that have utilized this method to improve forecasting performance.

2.3 Tuning of forecasting models

One of the most commonly used techniques for hyperparameter tuning in various forecasting models is Trial-and-Error. However, this approach can be computationally intensive and does not guarantee improved solutions [36]. An alternative approach gaining popularity is metaheuristics, which efficiently provide suitable hyperparameter sets in less computational time. Numerous metaheuristic methods have been proposed in the literature. For instance, the authors [37] reviewed several metaheuristic approaches to optimize hyperparameters such as the number of neurons, activation functions, and weights in forecasting models. Another study [38] compared Grid Search (GS), Random Search (RS), and Genetic Algorithm (GA) for tuning hyperparameters in Convolutional Neural Network (CNN) architectures. Their findings indicated that GS and RS are effective for small to medium datasets, while GA excels with larger datasets due to its higher accuracy and faster computational time. Lastly, the authors [39] applied Akaike Information Criterion (AIC) and Grid Search (GS) to optimize hyperparameters for forecasting PM 2.5 levels using ARIMA and hybrid ARIMA models. They reported that hybrid ARIMA achieved approximately 99

Moreover, we have compiled a list of relevant publications that explore the intersection of demand forecasting, focusing on both single and multiple products, and PI distribution aspects in Table 1.

Table 1: *The list of existing publications in relevant forecasting techniques and PI distribution aspect during the years 2014 – 2023.*

Dataset of different products	Forecasting types		Hybrid model	Product types		PI network
	Single model	Multiple model		Single product	Multiple product	
Electronic products[40]	X		N/A		X	
Transported requests[31]	N/A	N/A	N/A		X	X
Agricultural product[22]	X		N/A		X	
Train passenger[34]		X	LSTM-SVR	X		
Electricity price[41]	X		N/A	X		
Housing sales [33]		X	LSTM-ARIMA	X		
Smart locker banks[3]	N/A	N/A	N/A		X	X
Electricity [35]		X	ANN-ES3		X	
Agricultural product[7]	X		N/A	X		X
Traffic pattern[23]		X	LSTM-SVR	X		
Electronic product[42]	X		N/A	X		
Structural damage trends[19]		X	LSTM-SVR	X		
Our proposed study		**X**	**LSTM-dynamic baselines**		**X**	**X**

2.4 Research gaps

Despite the existing studies, as mentioned in Table1, have explored the concept of demand forecasting in PI distribution networks, several research gaps have been identified.

- Firstly, many studies propose single forecasting models, including traditional and neural network models, to forecast future demand. However, most of these studies focus either on forecasting for a single product or on applying the same forecasting model across all products. Additionally, in hyperparameter tuning, several works tend to optimize hyperparameters using a single technique within the forecasting model.
- Secondly, few studies have focused on integrating demand forecasting with PI distribution networks for specific products. Existing research typically applies a single forecasting model to forecast future customer demand and constructs PI distribution networks based on a single product, often with a limited number of PI-nodes, and restricts experimentation to rural areas only.

These gaps highlight opportunities for future research to explore more diverse forecasting models, integrate multiple products into PI distribution network designs, and expand experimentation into urban and diverse geographical contexts.

The prior study [7] described that several single baseline and LSTM neural network models were proposed for a basic PI distribution network focusing on agricultural products. Building upon these findings, this study extends its approach by addressing the following research gaps. Firstly, we elaborate on hybrid forecasting models that combine LSTM and baseline models. These models aim to analyze customer behavior trends across multiple products and reduce the forecasting error compared to baseline models [13]. The main differences between the proposed hybrid model in prior work and the model developed in this study lie in the number of hybrid combination patterns and the dynamic configuration of model hyperparameters. In this study, multiple hybrid patterns are considered, each characterized by different structures of alpha parameters that combine the forecast results from single models, along with their corresponding optimized alpha solutions. In contrast, the prior work focused on only one hybrid pattern with a single optimized alpha solution. Furthermore, in this study, both hyperparameter tuning and model hybridization are dynamically selected based on the validation performance of forecast demand for each product. Secondly, the forecasted demand from the first contribution, along with other related factors, will generate the list of suitable PI-hubs to create the flexible PI distribution network. A real-world case study involving electronic products from Thailand is conducted to evaluate the forecasting and distribution performance across two main regions: Bangkok and its metropolitan area, and the Central-Eastern regions. Detailed insights into the research contributions will be provided in the next section.

3. METHODOLOGY

In this section, the structure of the proposed hybrid forecasting models for multiple products in the PI distribution network is detailed. Figure 4 presents the flowchart of our proposed approach, which comprises two stages. The first stage involves creating and testing different hybrid forecasting models. Our approach focuses on selecting the appropriate hybrid model with automated hyperparameter tuning for each product item. The second stage dynamically generates a list of suitable PI-hubs to inform the design of the PI distribution network. To highlight the performance of the PI distribution with respect to transportation indicators, a comparison is made with the Classical distribution network. All details are described below.

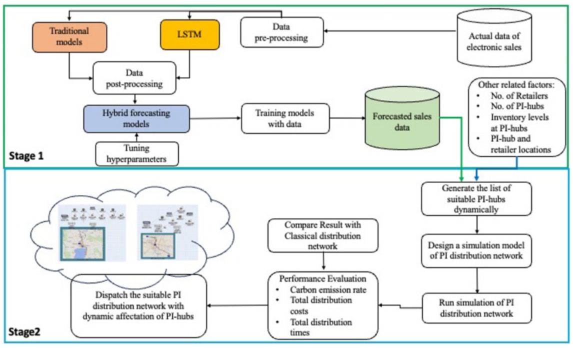

Fig.4: *The flow chart of our proposed approach.*

3.1 Stage 1: Forecasting models

3.1.1 Data Preparation

In our case, the dataset is forecast daily demand of four online electronic SKUs from a previous study [13]. The considered demand period is from 1 January to 31 December 2022. Previous steps, including data pre-processing, training the list of single forecasting models, and data post-processing, have been outlined in the previous study. All missing values and typographical errors are validated by the data cleaning step, which is a part of data pre-processing. The forecast demands for each SKU are selected based on the best performance of traditional models and a single LSTM model. For example, for SKU No.1, the SVR model provides the best performance among traditional models. Therefore, we used the forecast demand based on both the SVR model and the single LSTM model. These forecast demands are then divided into two sets: 70% for training and 30% for testing. This ratio was chosen through trial-and-error with different percentages and was found to provide the lowest error. These forecast demands are randomly split using a 10-fold cross-validation technique to avoid both underfitting and overfitting. Additionally, every single model's hyperparameters are tuned separately. For example, the hyperparameters for the single LSTM model, such as the number of layers (range 1-3 layers), number of neuron units (range 32-256 units), activation functions (such as elu, sigmoid, tanh), optimizers (such as nadam, rmsprop, adagrad), and the number of epochs (range 100-500 epochs) are optimized using the hybrid genetic and scatter search heuristics [7]. Meanwhile, hyperparameters such as trend and seasonal components are tuned using greedy search heuristics.

3.1.2 Creating Hybrid Forecasting Models

The objective is to develop new hybrid models to forecast future demand that account for nonlinear trends and seasonality. Inspired by existing studies [19], [35], we propose hybrid equation models in three formats. The details are shown below in Equations 20 – 22, each with different hyperparameter optimizations. For the traditional model in each equation, it can be dynamically chosen from the proposed lists.

First hybrid model (Hb_T1):

$$Y_t^{Hybrid} = (\alpha * Y_t^{LSTM}) + ((1-\alpha) * Y_t^{Trad}) \quad (20)$$

$\alpha =$ GRG Nonlinear; $0 \leq \alpha \leq 1$

Second hybrid model (Hb_T2):

$$Y_t^{Hybrid} = (\alpha * Y_t^{LSTM}) + ((1-\alpha) * Y_t^{Trad}) \quad (21)$$

$\alpha = \frac{\sum (Y_t^{LSTM} - Y_t^{Trad}) * (Y_t^{Actual} - Y_t^{Trad})}{\sum (Y_t^{LSTM} - Y_t^{Trad})^2}$; inspired by [35]

if $\alpha < 0$; $\alpha = 0$ or $\alpha > 1$; $\alpha = 1$

Third hybrid model (Hb_T3):

$$Y_t^{Hybrid} = (\alpha * Y_t^{Trad}) + ((1-\alpha) * Y_t^{LSTM}) \quad (22)$$

$\alpha = \frac{\sum (Y_t^{LSTM} - Y_t^{Trad}) * (Y_t^{Actual} - Y_t^{Trad})}{\sum (Y_t^{LSTM} - Y_t^{Trad})^2}$; inspired by [35]

if $\alpha < 0$; $\alpha = 0$ or $\alpha > 1$; $\alpha = 1$

Subject to:

Y_t^{Actual} = Actual data at period t

Y_t^{Hybrid} = Forecast data of the hybrid model at period t

Y_t^{LSTM} = Forecast data using the LSTM model at period t

Y_t^{Trad} = Forecast data using the traditional model at period t

For hyperparameter tuning procedures of different hybrid models, we tune only the alpha hyperparameter, which is tuning by GRG nonlinear for Hb_T1 model or inspired formulations as shown in Hb_T2 and Hb_T3 models. For GRG nonlinear, the suitable alpha with the range from 0 to 1 will be optimized by GRG nonlinear method based on the lowest MAPE score between actual and forecasted demands.

3.1.3 Training Data with Hybrid Models

After creating the hybrid forecasting models, the forecast demand from the data preparation step will be trained using the three hybrid models. These hybrid models aim to improve accuracy and reduce demand variation through hyperparameter tuning. In this case, alpha (α) is chosen as the hyperparameter to optimize each hybrid model using different optimization techniques.

3.1.4 Forecasting Evaluation

Performance evaluation is conducted using two indicators: accuracy and demand variation. Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scale Error (MASE) are chosen to evaluate accuracy. To assess demand variation, the Coefficient of Variation (CV) score is used (Peterson and Silver 1985). If the CV score is less than 0.25, it indicates that the demand pattern is stable with minimal variation, even when projected into future time steps. The testing set of forecasted demand will be evaluated using these tools to determine the forecasting performance.

After completing all the steps above, the forecasted demand for electronic SKUs will be used as an input factor in the PI distribution simulation. Detailed descriptions of this process are provided in the next section. Additionally, our study validates the performance of hybrid forecasting models using the dataset of agricultural products from a previous study [7]. The objective is to assess the performance improvement of hybrid models in different contexts.

3.2 Stage 2: PI distribution network modelling

3.2.1 Data Preparation

We select the forecasted demand for each electronic SKU based on the best-performing hybrid model from the previous stage. The forecasted demand is then prepared and imported as one of the input parameters for the simulation. In this study, all electronic SKUs are assumed to be products within the distribution network. All electronic SKUs are also contained in different box sizes. Moreover, the forecasted demand is combined with other related factors, such as the number of retailers, the number of PI-hubs, the inventory levels at PI-hubs, and PI-hub and retailer locations, to generate the list of suitable PI-hubs to inform the design of dynamic PI distribution networks.

3.2.2 Creating Distribution Networks

In this study, we design the PI distribution network and a benchmark using Google Maps. The benchmark is the Classical distribution network. Moreover, the addressed problem was formulated through the mathematical model. For more details, see our previous study [45]. The description of stakeholders and assumptions for each distribution network are presented based on the limitation of electronic SKUs' specification in this study.

Scenario 1: Classical Distribution Network

- There are two groups of stakeholders: Bangkok and its metropolitan, and Central-Eastern regions. The lists are illustrated below.
  - Bangkok and its metropolitan area: One warehouse and four retailers
  - Central-Eastern regions: One warehouse, two retailers in the Central region, and two retailers in the Eastern region.
- All retailers in these two groups receive all products from the same warehouse.
- The product quantities at each retailer are sufficient to meet customer orders.
- Customers who order products via online channels must receive their orders at a closet retailer.
- The company uses only one truck with sufficient volume for each route.
- A truck for each route starts from the warehouse to distribute all products to various retailers. All products are assumed to be in one container.
- After completing product distribution, the truck for each route will return to the warehouse at the end of the day.

Scenario 2: PI Distribution Network

- There are two groups of stakeholders: Bangkok and its metropolitan area, and the Central-Eastern regions. The lists are illustrated below.
  - All regions: Three PI-hubs and six retailers
- PI-hubs can store all products as a warehouse and receive them as retailers.
- All retailers from different regions can share resources from the same PI-hub.
- All retailers in these two groups receive all products from any PI-hubs in the distribution network. All products are assumed to be in various PI-containers.
- The product quantities at each retailer are sufficient to meet customer orders.
- The stock levels of each PI-hub will be empty at the end of the day because we assume that the product quantities will be delivered to all customers completely.
- Customers who order products via online channels must receive their orders at a closet retailer.
- A truck for each route can start from any PI-hub to distribute all products to various retailers.
- A truck can return to any PI-hub after completing product distribution at the end of the day.

Additionally, we set up common parameters, such as travel time, loading time, unloading time, and the maximum capacity of each truck. All parameter configurations for Scenarios 1-2 are shown below.

- Travel time: 8:00 am – 5:00 pm
- Loading-Unloading time: 30 sec/box

- Max capacity: Truck container 1 = 55 boxes, Truck container 2 = 20 boxes
- Each truck has only one container that can contain all the boxes of SKUs

Figures 5 and 6 illustrate examples of Classical and PI distribution networks. Figure 5 demonstrates these networks for all experimental regions, while Figure 6 specifically shows these networks in Bangkok and its metropolitan area. In addition, the dispatch quantities for both scenarios will be flexible based on daily requests, and the PI container size will accommodate all daily demands.

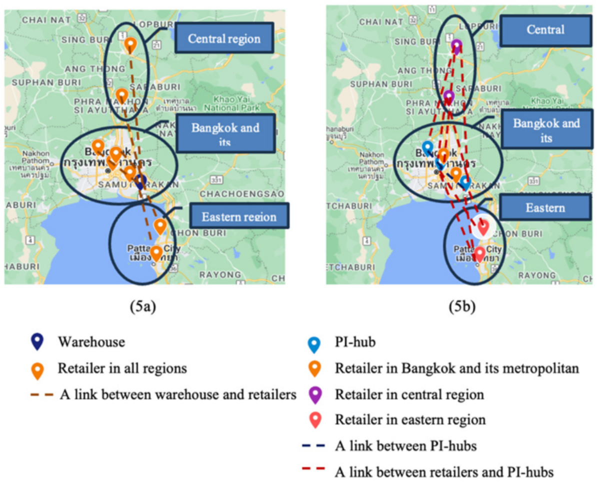

Fig.5: *The maps of Classical (5a) and PI (5b) distribution networks for all regions.*

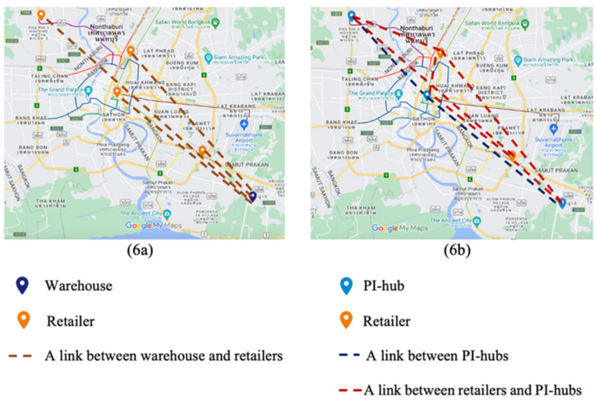

Fig.6: *The maps of Classical (6a) and PI (6b) distribution networks for Bangkok and its metropolitan area.*

3.2.3 Design Distribution Networks Through Simulation

In this study, the FlexSim simulation tool was used to design Classical and PI distribution networks based on the scenarios and figures from the previous step. The examples of the two simulation networks in Figures 7(a-b) are designed based on the distribution network in Figure 6. We create the distribution networks using Task Executors, Warehousing, and GIS libraries for these two scenarios with a fixed number of nodes. The simulation network design is inspired by [46], [47]. The list of network components in each scenario is shown below.

Region: Bangkok and its metropolitan area

Scenario 1: Classical Distribution Network

- A single warehouse consists of two components. The first component is a cross-dock point (Warehouse), and the second component is a returning point (Delivery_WH).
- Four retailers: Each retailer consists of two components. The first component is a checking point (Retailer_X), and the second component is a delivery point (Delivery_RX). X stands for the retailer order.
- Retailer_X: the loading and unloading points at Retailer X
- Delivery_RX: the storage area for unloaded products at Retailer X
- The last delivery point is created for a returning truck point at the warehouse

Scenario 2: PI Distribution Network

- Three PI-hubs: Each PI hub consists of two components. The first component is a cross-dock point (PI_Hub_X), and the second component is a delivery point (Delivery_PHX). X stands for the PI-hub order.
- Two retailers: Each retailer consists of two components. The first component is a checking point (Retailer_X), and the second component is a delivery point (Delivery_RX). X stands for the retailer order.
- The characteristic of checking and delivery points is the same as Scenario 1.
- All cross-dock points can share resources such as trucks, truck drivers, and storage spaces among them.

The central and eastern regions also design distribution networks with two PI-hubs and four retailers through a simulation program based on prior scenarios and the two distribution networks in Figure 5b. All components are similar to those in the simulation shown in Figures 7(a-b). The example of PI distribution network simulation in these regions is shown in Figure 7c.

3.2.4 Calculating all performance indicators

Upon completing the simulation of the product distribution network in all regions, we calculate the daily and total distribution times and costs using Equations 23-27. For all relevant parameters, such as daily weight and unit transport cost, the values are obtained from a company case study. Additionally, the distribution time and cost will be calculated for each scenario. Scenario 1, the Classical distribution, deliv-

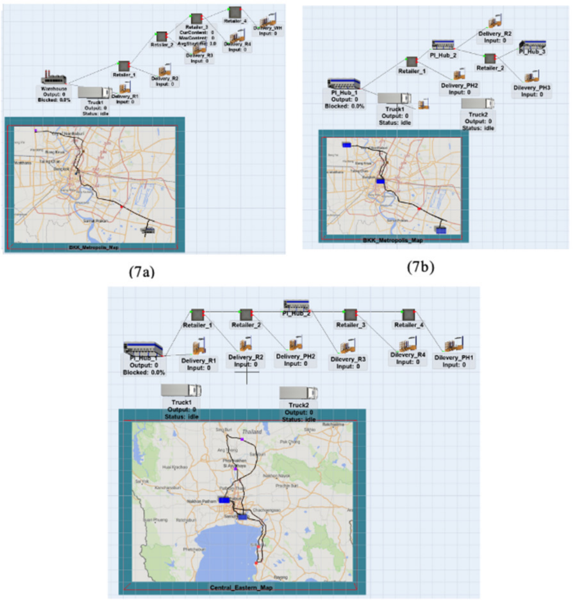

Fig. 7: *The simulation of the Classical distribution network (7a) and PI distribution network (7b) for Bangkok and its Metropolitan and PI distribution network (7c) for the Central and Eastern regions.*

ers all electronic SKUs with a single truck, while Scenario 2, which is the PI distribution, divides delivery orders into two trucks. Furthermore, we evaluate and compare the total carbon (CO_2) emissions, including relevant fuel parameters, between the Classical and PI distribution networks in this study, as shown in Equation 27 and inspired by [14], [48]. The objective is to reflect the environmental sustainability of the PI distribution network.

$$\text{Daily distribution time} = \text{daily loading time} + \text{daily unloading time} + \text{daily transport time} \tag{23}$$

$$\text{Total distribution time} = \text{daily distribution time} * \text{number of days} \tag{24}$$

$$\text{Daily distribution cost} = \text{daily transport distance} * \text{daily weight x unit transport cost (THB/Ton-KM)} \tag{25}$$

$$\text{Total distribution cost} = \text{daily distribution cost} * \text{number of days} \tag{26}$$

$$EM_{total} = FE * FC * \text{total transport distance} \tag{27}$$

Subject to:
EM_{total} = Total carbon emissions
FE = The fuel emission rate, equal to 2,621 grams/liter
FC = The fuel consumption rate, equal to 0.3462 liters/km

3.2.5 Calculating the deviation percentage with actual demand

The objective of this step is to measure the variation between forecasted and actual demands, ensuring the reliability and trustworthiness of the forecast demand. In this study, we calculate the deviation in both distribution time and cost between forecasted and actual demands. The deviation equations are shown in Equations 28-29, inspired by [7].

$$\text{Distribution cost deviation percentage} = (\text{Absolute (Total\_dist\_cost\_forecast} - \text{Total\_dist\_cost\_actual)/ Total\_dist\_cost\_actual)} * 100 \tag{28}$$

$$\text{Distribution time deviation percentage} = (\text{Absolute (Total\_dist\_time\_forecast} - \text{Total\_dist\_time\_actual)/ Total\_dist\_time\_actual)} * 100 \tag{29}$$

3.2.6 Analyzing and comparing the scenario performance

After finishing all the steps above, all results (distribution time, distribution cost, and deviation percentage) will be analyzed to provide both quantitative and qualitative findings.

4. RESULTS AND DISCUSSION

The proposed models are developed using Python programming language in Google collab and FlexSim simulation. Furthermore, the experiments of a company case study are validated on an Apple M1 CPU-based machine with 8GB of RAM DDR5, running Mac OS Sonoma version 14.4.1. The results of different forecasting models and the results of testing forecasted data on PI and Classical distribution networks are analyzed and discussed below.

4.1 Results of different forecasting models

This sub-section begins with the performance comparison between single forecasting models from a previous study [13] and hybrid forecasting models. In addition, based on the results of ES3 models from previous study, the additive and multiplicative patterns are considered as fixed values for the seasonal parameter depending on the SKU demand patterns. Therefore, we fix the value of this parameter in both additive and multiplicative forms. The comparison of different single models from our previous study is shown in Table 2.

Furthermore, the best results of single models from Table 2 are compared with the results from single LSTM and hybrid forecasting models in Table 3. The results in Table 3 illustrate that the first and second hybrid models (Hb_T1, Hb_T2) of electronic SKU 1 provide the best performance with the lowest MSE, MAE, and MAPE scores when compared with other hybrid and single models. For the MASE score, these two hybrid models deliver similar scores to a single LSTM model. The first and second hybrid models keep the same error scores for all indicators because they forecast output with the same alpha value. However, these two models calculate the alpha with different techniques. In addition, Figure 8a displays the comparison trends between the forecast and actual outputs of electronic SKU 1 for the testing data. We can see that the forecast outputs provide similar trends and seasons to the actual outputs.

Table 2: *The evaluation of forecasting performance for traditional single models from a previous study [13].*

Electronic SKUs	Model type	Forecasting Performance			
		MSE	MAE	MAPE	MASE
SKU 1	SVR	**70.040**	**6.257**	**31.930**	**0.893**
	ES3	122.014	8.413	37.127	1.196
	ARIMA	277.023	14.18	69.661	2.017
SKU 2	SVR	**13.279**	**2.878**	**30.598**	**0.810**
	ES3	17.657	3.246	40.758	0.951
	ARIMA	33.224	4.140	89.360	1.211
SKU 3	SVR	**6.823**	**2.069**	73.995	**0.790**
	ES3	11.243	2.534	**56.534**	0.931
	ARIMA	11.567	2.604	84.039	0.984
SKU 4	SVR	**5.978**	**1.751**	**67.401**	**0.791**
	ES3	6.807	2.021	74.987	0.917
	ARIMA	8.697	2.047	88.934	0.931

The results of electronic SKU 2 in Table 3 reveal that a single LSTM model provides the best performance with the lowest MSE, MAE, MAPE, and MASE scores when compared with other hybrid and single models. The second hybrid model (Hb_T2) has similar performance to a single LSTM model based on MSE, MAE, and MASE. In addition, Figure 8b displays the comparison trends between the forecast and actual outputs of electronic SKU 2 for the testing data. We can see that the forecast outputs show similar trends and seasons with actual outputs, although the gap between these two outputs is a bit larger than that for the SKU 1 output. Furthermore, the general patterns of these two SKUs are shifted by a few days. This phenomenon arises from the drastic increase in customer demands for online wireless gadget devices at the beginning of each week. One of the main reasons for this phenomenon is the weekly discount or early promotion offered for these devices.

The results of electronic SKUs 3-4 in the same table demonstrate that two hybrid models deliver the best performance, with the lowest MSE, MAE, MAPE, and MASE scores when compared to other hybrid and single models. For the electronic SKU 3, the second hybrid model (Hb_T2) has the best performance, based on the lowest MAE, MAPE, and

Table 3: *The evaluation of forecasting performance between single and hybrid models in SKU 1 – SKU 4.*

Electronic SKUs	Model type	Forecasting Performance			
		MSE	MAE	MAPE	MASE
SKU 1	SVR	70.040	6.257	31.930	0.893
	LSTM	55.801	5.380	26.661	0.765
	Hb_T1	55.678	5.335	26.458	0.771
	Hb_T2	55.678	5.335	26.458	0.771
SKU 2	SVR	13.279	2.878	30.598	0.810
	LSTM	11.765	2.720	29.480	0.791
	Hb_T2	11.834	2.729	29.575	0.796
SKU 3	SVR	6.823	2.069	73.995	0.790
	LSTM	7.673	2.060	60.680	0.790
	Hb_T2	7.529	2.026	60.236	0.772
SKU 4	SVR	5.978	1.751	67.401	0.791
	LSTM	5.570	1.680	61.680	0.763
	Hb_T1	5.429	1.641	61.205	0.765
	Hb_T2	5.429	1.641	61.205	0.765

MASE. Similarly, with the electronic SKU 4, the first and second hybrid models (Hb_T1, Hb_T2) provide the best performance with the lowest error in the three indicators. Regarding the performance comparison between single and hybrid forecasting models, we can observe that two hybrid models (Hb_T1 and Hb_T2) are the most efficient based on the forecasting performance of the four SKUs. The error reduction arises not only from the formulation of hybrid forecasting equations but also from the impact of the alpha hyperparameter, which utilizes both GRG Nonlinear and the alpha calculation formula, which is inspired by [35].

After completing the evaluation of accuracy performance for the four SKUs mentioned above, we proceed to evaluate the demand variation using the CV score. The CV score of the proposed data should be less than 0.25, indicating less fluctuation in demand, which allows the company to effectively manage inventory levels and distribution plans with customers. The results in Table 4 show that all electronic SKUs have a CV score lower than 0.25. This indicates that all forecasted electronic SKUs can be implemented to manage distribution resources in the company's case study.

Table 4: *The list of best performance forecasting models in all electronic SKUs.*

Electronic SKU	Best performance model	Hybrid combination	CV score
SKU 1	Hb_T1, Hb_T2	LSTM-SVR	0.04
SKU 2	Single LSTM	N/A	0.03
SKU 3	Hb_T2	LSTM-SVR	0.13
SKU 4	Hb_T1, Hb_T2	LSTM-SVR	0.02

Regarding the results in Table 3 above, we can see that some electronic items, such as SKU 1 and SKU 2, maintain low error scores, while SKU 3 and SKU 4 exhibit high error scores. This phenomenon suggests that SKU 1 and SKU 2 have less fluctuation than

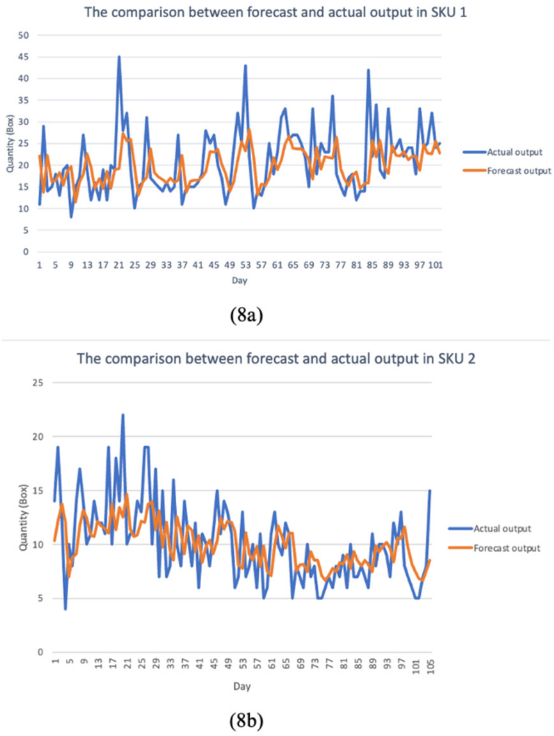

Fig.8: *The comparison of the electronic trends in forecast and actual output of SKU 1 (8a) and SKU 2 (8b).*

Table 5: *The evaluation of forecasting performance between single models: SVR, MLR, ARIMAX, and LSTM, in [7], and the proposed hybrid models.*

Forecasting model	**Data with time lag2**			
	RMSE	MAPE	MAE	MASE
SVR	152.31	11.15	**100.46**	**0.850**
MLR	153.04	11.25	101.87	0.862
ARIMAX	331.29	41.98	103.11	0.873
LSTM	158.45	12.18	106.90	0.905
Hb_T1	152.33	**11.12**	100.63	0.885
Hb_T2	**152.19**	11.13	100.47	0.883
Forecasting model	**Data with time lag4**			
	RMSE	MAPE	MAE	MASE
SVR	150.92	11.11	98.38	**0.832**
MLR	150.25	11.00	99.71	0.843
ARIMAX	150.26	11.04	99.82	0.844
LSTM	150.91	11.18	99.52	0.842
Hb_T1	148.71	**10.99**	97.35	0.856
Hb_T2	**148.64**	11.00	**97.34**	0.856
Forecasting model	**Data with time lag6**			
	RMSE	MAPE	MAE	MASE
SVR	151.14	11.10	98.35	0.831
MLR	150.16	10.97	99.56	0.841
ARIMAX	150.15	11.00	99.75	0.843
LSTM	149.24	10.97	98.05	**0.829**
Hb_T1	148.17	**10.93**	**97.07**	0.854
Hb_T2	**148.12**	10.94	97.12	0.854

SKU 3 and SKU 4. One of the limitations of this experiment is the number of training and testing historical data points. The company case study provides experimental data for only one year (approximately 255 daily training and 105 daily testing outputs). Therefore, to validate the performance of the hybrid forecasting models, we will assess the model performance using other datasets of agricultural products from our previous study [7]. The results in Table 5 show that our hybrid models (Hb_T1, Hb_T2) perform better for data with time lag 4 and 6, while these hybrid models offer similar performance to an SVR model for the data with time lag 2. In addition, the number of historical data points impacts the error scores of training and testing data. A recurrent neural network model, such as LSTM, is suitable for a large amount of training and testing data. As can be seen from the results in Table 5, the hybrid models deliver lower error scores than the results in Table 3. This experiment can confirm that the hybrid models can work well with the large amounts of datasets.

4.2 Results of testing forecasted data on PI and Classical distribution networks

The forecast outputs for electronic SKU 1 to SKU 4 products will serve as input factors, measured in terms of quantity (boxes), in the distribution network. This study involves designing Classical and PI distribution network models for all regions using the FlexSim simulation tool, based on parameters configured in the research methodology section. Initially, we will present the simulation results for Bangkok and its metropolitan distribution network. Subsequently, we will describe the simulation outcomes for the Central-Eastern distribution network. The objective is to validate the performance of both Classical and PI distribution networks in both urban and rural geographical contexts. In addition, the number of PI hubs in both Bangkok and its metropolitan areas, and the Central-Eastern regions are generated dynamically based on the forecasted demand and other related factors as mentioned in section 3.2.3. The experimental periods in this study are set to 7 days and 14 days, as some SKUs plan delivery volumes on every week, while others plan deliveries every two weeks.

First region: Bangkok and its metropolitan area

Figure 9a represents the number of boxes in each SKU over 7 days across all retailers and PI-hubs in Bangkok and its metropolitan area. The results from Figure 9a are used to calculate the total distribution time and cost for Classical and PI distribution networks.

The results in Figure 9b represent the evaluation of distribution performance between Classical (Scenario 1) and PI (Scenario 2) distribution networks over 7 days in Bangkok and its metropolitan area. We can see that the distribution time and total cost for Scenario 2 are less than those for Scenario 1 each

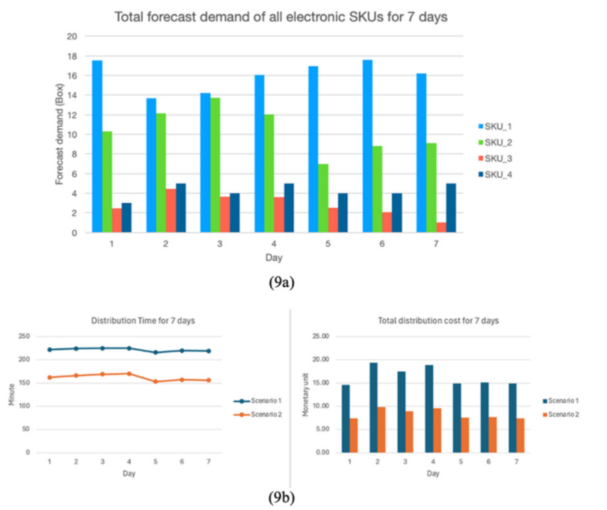

Fig.9: *The total forecast demand of all electronic SKUs (9a) and the comparison of the distribution time and cost between Classical and PI distribution networks (9b) over 7 days in Bangkok and its metropolitan area.*

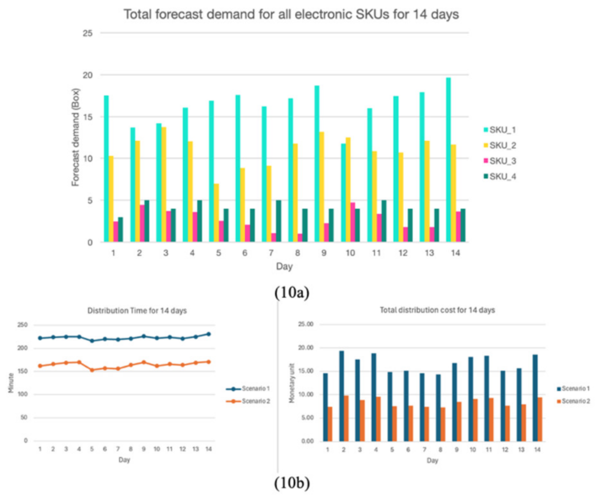

Fig.10: *The total forecast demand of all electronic SKUs (10a) and the comparison of the distribution time and cost between Classical and PI distribution networks (10b) over 14 days in Bangkok and its metropolitan area.*

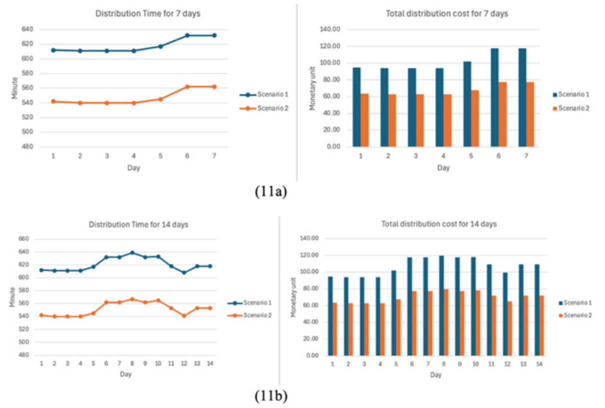

Fig.11: *The comparison of the distribution time and cost between Classical and PI distribution networks over 7 days (11a) and 14 days (11b) in the Central-Eastern regions.*

day. The average improvement percentage after implementing the PI distribution network is around 27 percent.

Moreover, we calculated the total quantity of all electronic SKUs for 14 days in the same region. Figure 10a represents the number of boxes in each SKU over 14 days. The results from Figure 10a are used to calculate the total distribution time and cost for Classical and PI distribution networks. Then, we simulated the Classical (Scenario 1) and PI (Scenario 2) distribution networks for 14 days and displayed the results in Figure 10b. We can see that the distribution time and total cost each day for Scenario 2 are less than those for Scenario 1. The average improvement percentage after implementing the PI distribution network is around 26.4 percent. When considering the trends of distribution time and cost, we can find that the PI distribution network can reduce total distribution time and cost in both short and long periods.

Second region: Central-Eastern regions

The results in Figure 11a represent the evaluation of distribution performance between Classical (Scenario 1) and PI (Scenario 2) distribution networks over 7 days across all retailers and PI-hubs in the Central-Eastern regions. We can see that the distribution time and total cost in each day in Scenario 2 are lower than Scenario 1. The average improvement percentage after implementing the PI distribution network is around 11.4 percent.

Moreover, we calculate the total quantity of all electronic SKUs over 14 days in the same region. These quantities are used to calculate the total distribution time and cost for Classical and PI distribution networks. Then, we simulate the Classical (Scenario 1) and PI (Scenario 2) distribution networks for 14 days and display the results in Figure 11b. We can see that the distribution time and total cost each day for Scenario 2 are lower than for Scenario 1. The average improvement percentage after implementing the PI distribution network is around 11.1 percent. When we consider the trends in distribution time and cost, we find that the PI distribution network can reduce total distribution time and cost in both short and long periods.

Based on the results from the two regions, the PI distribution network (Scenario 2) demonstrates better performance than the classical distribution network (Scenario 1), even though both networks have the same total number of nodes. One of the main reasons for this improvement is the presence of additional PI-hubs and more seamless route connectivity within the network. First, some retailers can be transformed into PI-hubs because they have sufficient space and facilities to function as cross-docking points. Second, under the PI paradigm [49], vehicles can travel seamlessly from any retailer to any PI-hub. In addition, vehicles can start from one PI-hub and end at a different PI-hub at the end of the day. As a result, the total distribution time and cost in the PI distribution network are lower than those in the classical distribution network.

4.3 Managerial Aspect

This study not only focuses on the evaluation of distribution performance via distribution cost and time but also calculates the total distances and total carbon emissions, which are essential for the managerial aspect in the logistics and distribution sector. The results in Table 6 display the comparison of total distances in both Classical (SC1) and PI (SC2) distribution networks in both regions. The results show that Scenario 2 provides a shorter distance than Scenario 1 by approximately 13.6 percent. The shorter distance impacts the total carbon emissions, as displayed in Table 6. The results also reveal that Scenario 2 can reduce carbon emissions by around 13.6 percent compared to Scenario 1.

Table 6: *Comparison of all relevant indicators between Classical and PI distribution networks.*

Indicator	Period (days)	BKK Metropolitan		Central- Eastern	
		SC 1	SC 2	SC 1	SC 2
Total distance (KM)	7	1,026.99	609.89	4,743.06	4,097.10
	14	2,053.98	1,219.18	9,486.12	8,194.20
Total carbon emission (KG)	7	931.88	553.41	4,303.81	3,717.67
	14	1,863.76	1,106.27	8,607.61	7,435.34

Then, we calculate the improvement percentage in all aspects, such as total distance, total carbon emission, distribution time, and distribution cost. After implementing Scenario 2, we see that the PI distribution network reduces the total distance and total carbon emissions by around 40.6 percent for Bangkok and its metropolitan area, and by 13.6 percent for the central-eastern regions. For the distribution time, Scenario 2 decreases the distribution time by around 26-27 percent for Bangkok and its metropolitan area, and by 11 percent for the central-eastern regions. Finally, for distribution cost, we see that the PI distribution reduces the total cost by approximately 49 percent in both 7 days and 14 days for Bangkok and its metropolitan area, and by around 34 percent for the central-eastern regions. All details are represented in Table 7.

Then, this study calculates the distribution time and cost deviations between forecast demand and actual demand. We calculate these deviations in both

Table 7: *Comparison of all relevant indicators between Classical and PI distribution networks.*

Period		7 days	14 days
% Distance improvement	BKK	40.6	40.6
	CE	13.6	13.6
% Carbon emission improvement	BKK	40.6	40.6
	CE	13.6	13.6
% Distribution time improvement	BKK	27.0	26.3
	CE	11.4	11.1
% Distribution Cost improvement	BKK	49.5	49.3
	CE	33.5	33.8

Scenario 1 (Classical) and Scenario 2 (PI). The results show that both distribution scenarios provide low variation, approximately 1-2 percent, except for the cost deviation in the Central-Eastern regions, which is around 9-18 percent. This implies that the trends in forecast demand are similar to the trends in actual demand. Therefore, the company in the case study can manipulate some relevant resources using forecast demand. Additionally, we propose the managerial framework of resource strategic planning. All details are demonstrated in Figure 12.

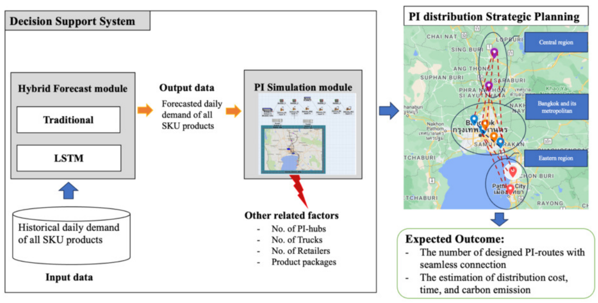

Fig.12: *The managerial framework of resource strategic planning.*

The managerial framework above illustrates the relationship between the Decision Support System (DSS), which consists of the hybrid forecasting and PI simulation modules, and the PI distribution strategic planning. The DSS generates an appropriate distribution plan based on the forecasted daily demand of all SKU products and related factors, such as the number of PI-hubs, trucks, retailers, and product packages. The forecast results are generated by selecting the hybrid model with the smallest error gap, as shown in Figure 13, after comparing the error gaps among all hybrid models. The number of designed PI-routes, along with the estimated distribution cost, time, and carbon emissions from the strategic plan, would be dynamic and flexible, depending on the output from the DSS. Therefore, the managerial framework can help managers make better decisions.

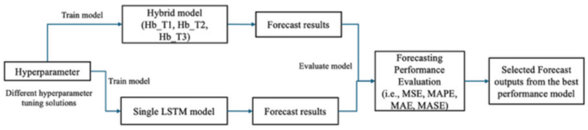

Fig.13: *The flowchart of forecasting models' selection.*

5. CONCLUSION

This study focuses on the performance of hybrid forecasting for multiple products in the PI distribution network. Firstly, we implement hybrid forecasting models, which combine traditional and LSTM neural network models, to enhance the forecasting performance regarding both accuracy and demand variation of electronic products. A company case study in Bangkok, Thailand, is chosen to assess the models. The results show that hybrid models provide the best performance for three SKUs, while only one SKU performs well with a single LSTM model. The appropriate hybrid combination of forecasting models is chosen based on each electronic SKU item. Moreover, all SKUs respond to low values of the Coefficient of Variation (CV) score, indicating that the forecasted demands of electronic sales are less fluctuating and more reliable. Secondly, we combine the forecasted demand with other related factors to generate the dynamic PI distribution network through simulation. The objective is to improve the distribution performance of electronic products and compare the results with the Classical distribution network. The results reveal that the PI distribution network can reduce the distribution distance, time, and cost by approximately 41%, 26%, and 49% for Bangkok and its metropolitan area, respectively. In the Central-Eastern regions, these parameters decrease by around 14%, 11%, and 34%. Additionally, carbon emissions in the distribution network decreased by around 41% for Bangkok and its metropolitan, and by around 14% for the Central-Eastern regions after implementing the PI distribution concept. Furthermore, the deviation percentage of both distribution cost and time between forecasted and actual demands is very small, approximately 1-2%, except for the cost deviation in the Central-Eastern regions, which is around 9-18%. This indicates that the forecasted demand can be implemented for resource planning in the distribution process. Although forecasting accuracy gains are sometimes small, the main contribution lies in the resulting improvements in distribution distance, time, and cost.

For future work, we plan to test sales forecasting under perturbation scenarios of the PI network (e.g., accidents, congestion, natural disasters). Moreover, for the PI distribution network of the company case study, electronic products are made to order and operated under a pull system. This means that the company prepares sufficient orders to meet daily demand. However, if this assumption is relaxed—for example, if some retailers retain inventory at the end of the day—additional holding costs may be incurred at the retailer level. This scenario will be examined in future studies. In addition, service contracts that allow for order swapping will be extended to be implemented in the PI distribution network.

DATA AVAILABILITY STATEMENT (DAS)

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available because they contain information that could compromise the privacy of research participants.

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