A New Product's Demand Forecasting Using Artificial Neural Network

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Abstract: This paper presents the means to improve new product (mobile phone) demand forecasting that led to total cost reduction and more efficient inventory management. The selected forecast methods, namely Holt-Winters (HW), Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), and Artificial Neural Network (ANN), are implemented, where the most accurate method, ANN is selected to forecast demand of the new product (sixth generation mobile phone) for the following year. In addition, the comparison between the original and ANN method shows that ANN is 51.28% more accurate. After that, we develop the proposed solution plan that links improved demand forecasting to calculate the suitable inventory quantities and production rates for both finished goods and work in process. The proposed solution scenario when compared with problem scenario can reduce loss sales and inventory carrying costs by $1,400,626.80 or equivalent to 27.71%.

1 INTRODUCTION

Demand forecasting is a prediction of product demand or service demand for a period in the future. It relies on historical demand data using mathematical techniques to obtain appropriate forecasting methods and accurate forecasting values. These precise demand forecasts result in effective planning, whether it is planning the use of resources such as machinery, personnel, as well as purchasing raw materials necessary to produce finished goods. Therefore, if there is a lack of accurate forecasting, it may affect the productivity of the whole production line. In addition to that, in terms of inventory management for retail stores, inaccurate demand forecasting can have far-reaching negative consequences. For instance, ordering more products than customers need will result in the problem of deterioration of products, especially perishable products such as fruits or fresh food. In addition, when we store these overordered products for too long, we may end up disposing of them as waste. In addition, it may lead to the problem of overstocking in warehouse management causing loss without cause of necessary storage space. On the other hand, inaccurate demand forecasts can also result in shortages, which is why accurate forecasting is essential.

The research will focus on finding suitable forecasting methods using time-series data analysis for the case study of the company's upcoming new mobile phone products. At present, there is still a problem of insufficient products to meet the needs of customers. This originates product shortages causing customers to wait for products for a long time and causing customers to change their minds to buy products from competing companies, resulting in loss of customers and revenue. By looking into past data, it shows product shortages and customer waiting times of 8-10 weeks, see Table 2. Therefore, case study companies want to analyse historical data to solve such problems in releasing new products to the

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market for the following year. The remainder of this paper is structured as follows. Firstly, section 2 presents the objectives of this research and section 3 presents related literature. Then, section 4 presents research methodology where in-depth problem analysis and proposed methodology are explained. Continued to section 5, results of the experiment are presented to verify the superiority of the proposed methodology (forecasting using ANN). Lastly, section 6, summary, discussion, and future research perspectives are concluded and presented.

2 OBJECTIVES

The objectives of this research are twofold; first to conduct in-depth analysis on the current loss sales problem of a mobile phone manufacturer and second to find the means to solve such problems and demonstrate the improvement results.

3 RELATED LITERATURES

Normally, we can divide forecasting methods into three main categories, namely traditional statistics, machine learning based, and hybrid methods, (Ingle et. al., 2021) where we summarize those related literatures as follows.

3.1 Traditional Statistical Forecasting Method

Most traditional methods use historical sales data to make forecasts of future demand. It uses time series analysis methods, namely Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), and Holt-Winters. We briefly summarize these research works as the following paragraphs.

Ghosh (2020) forecast food demand using ARIMA model, where the ideal model is ARIMA (1,0,1). In their work, they use Akaike, Schwarz Bayesian, Maxi-mum likelihood, and Standard Error to evaluate accuracy of forecasting.

Huber et. al. (2017) forecast demand in a hierarchical pattern at different organizational levels where they use multivariate ARIMA model to forecast daily demand for the bakery supply chain. They find out that ARIMA is effective and can reduce the problem of inaccurate forecasting.

Silva et. al. (2019) make demand forecast for the food industry. They show that Exponential smoothing method is an accurate and easy-to-use method for improving production planning effectively.

Kimes et. al. (1998) predict the demand for various menu dishes in a restaurant. They show that the Holt-Winters model can effectively forecast these demands that have both seasonal variation and trend characteristics.

Sinthukhammoon et. al. (2023) forecast the demand of Okra for planting community enterprise located in Kamphaeng Saen District, Thailand. The forecast methods implemented in their study are Exponential Smoothing with trend and Seasonal index. The result shows that Seasonal index method provide lesser error therefore selected to forecast the next year Okra demand data.

3.2 Machine Learning Based Forecasting Model

Machine learning (ML) models use algorithms that learn from data over time in an automated form. When compared with traditional forecasting, it is more accurate, flexible, and easily adjusted according to various situations, however, traditional methods are much easier to understand and use. Well known ML models are Regression, Decision Tree, and Deep Learning. We summarize the related literatures as follows:

Reynolds et. al. (2013) make forecasts for future sales in the restaurant industry. In their research, they implement multiple regression (MR) model constructed based on 41 years past sales data, where the presented models were precise and acceptable.

Ma et. al. (2016) perform demand forecasting in case of high dimensional data for retail product SKUs. The results show that the use of Multi stages Lasso regression (LR) plays a significant role in selecting variables and estimating models. However, the main problem with LR is that the explanatory variable space will increase rapidly if we include promotional matching data in the forecast model.

Priyadarshi et. al. (2019) implement forecasting models such as ARIMA, long short-term memory (LSTM) networks, support vector regression (SVR), and gradient boosting regression (GBR) for forecasting selected vegetables demand. The results show that the machine learning algorithms, namely LSTM and SVR provide more accurate forecasting when compared to other models.

Ramya and Vedavathi (2020) implement XG Boost algorithm to predict Rossmann sales data over eight thousand drug stores. The result shows that XG Boost gives an excellent sales forecast over ARIMA, in addition it can assist shops to increase income by analysis of extra information such as advertisement recommendations, holiday, and competitors.

In addition, there are works that implemented a hybrid forecasting method where the use of a system consisting of more than one method together. For example, Aburto and Weber (2007) used hybrid model between ARIMA and Neural Network models to forecast daily product sales. By using ARIMA outputs as input into Neural Network model, the results can give more accurate predictions.

3.3 ANN Based Model

Nuanmeesri et. al. (2022) present the combination of Multilayer Perceptron Neural Network with feature selection method to predict students drop out during COVID-19 pandemic of Suan Sunandha Rajabhat University. The results show that the proposed method gives the prediction accuracy of 96.98%.

Luckyn and Alabere (2024) determine the sale of diapers within the retail sector using ANN, where their historical data contain seasonality patterns, promotion activities, economic indicators, and demographic characteristics. The results show that the ANN can predict diaper sales with high accuracy and improve consumer satisfaction by decreasing stockouts and overstock situation.

Rumbe et. al. (2024) introduce two distinct approaches namely Holt-Winter method and ANN to forecast tent sales under seasonal influences. The results show the superiority of ANN over Holt-Winter method. In addition, the paper explores influential factors affecting commercial tent sales and identifying key supply chain players.

Binesh et. al. (2023) propose advanced recurrent neural network (LSTM) against five traditional forecasting models to forecast hotel room price under COVID-19 pandemic situation. The results show that the LSTM outperform traditional methods such that the simplest LSTM model is more accurate than that of the traditional methods.

Raza (2017); Fischera and Kraussb (2017); Xiong et. al. (2015), use deep learning to predict financial markets in terms of stock market performance, stock price, and stock volatility, respectively. The results show that for nonlinear and large volumes data, deep learning methods, namely long short-term memory (LSTM), artificial neural network (ANN), and generative adversarial networks (GAN), have proven to be more accurate forecasts compared to traditional statistical methods or other machine learning methods. Somehow, one important disadvantage of deep learning is that it adds computational complexity and require understanding and computer programming capabilities.

According to the literature review, the forecasting method suitable for our research will be the statistical forecasting method mentioned in section 2.1 and the Neural Network method (section 2.2), due to main reasons explained as follows.

1. Firstly, in our research the entrepreneur is interested in only forecasting one variable, namely the new product demand. Therefore, for simplicity it is not necessary to use complex multi variables forecasting methods such as decision tree-based method or regression analysis.
2. Secondly, demand data is stable and clearly formatted,
3. Lastly, in our research the entrepreneur needs forecasting methods that are more convenient to use and easy to understand over those complex methods.

4 RESEARCH METHODOLOGY

This research will begin by thoroughly exploring the problem to study the root cause of the problem, collect the necessary data for analysis, then conduct analysis to find solutions to problems. After that, we conduct experiments to determine the comparison results of before and after solving the problem. Finally, we will propose appropriate measures to solve the problem, explaining in detail for each step as follows:

4.1 In-Depth Problem Analysis

For in-depth problem analysis, we collected historical data to understand what happened during the release of last year's products (sixth generation) to market. Table 1 shows the data of such events.

Table 1 shows underestimation of demand forecasts every week except in week one. This causes the customer to not receive the product, resulting in the cancellation of the order or not placing an order. Table 2 shows the impact of this problem on false production planning.

From Table 2, we can identify significant problems, namely, insufficient finished goods stock, from week fifty-one to week eight, to meet either actual demand or forecast. This might originate from lacking connection among forecasts, production, and inventory planning. Moreover, finished goods (FG.)

Table 1: Historical data of mobile phone released to the market last year (sixth generation).

Week	Demand (Units)	Forecast (Units)	Deviation
50	237,450	210,000	-27,450
51	177,440	150,000	-27,440
52	112,116	100,000	-12,116
1	63,883	75,000	11,117
2	28,614	26,000	-2,614
3	20,573	15,000	-5,573
4	16,408	11,000	-5,408
5	9,550	8,500	-1,050
6	6,561	5,000	-1,561
7	4,159	3,500	-659
8	3,108	2,600	-508
9	2,770	2,600	-170

capacity and work in process (WIP.) capacity are insufficient to meet the level of market demand, either forecasted or actual demand.

The main reason of the insufficient FG. stock problem stems from in-accurate forecasting led to mis-planning of both FG. and WIP inventory volumes. Accordingly, we examine the comparison data between (see Table 1.) forecast and actual sales of sixth generation mobile phones, we can calculate the average percentage of absolute error (MAPE) is as high as 16.46%. As a result of high MAPE, we must improve demand forecast accuracy by finding a better forecast method than the original method for product demand. Noted that, the mobile phone demand has a combination of both trend and seasonal variation.

4.2 Forecasting Methodology

To achieve the objective mentioned above we implement various forecasting methods as:

- Holt-Winter's model (HW)
- ARIMA
- Exponential Smoothing (ETS)
- Artificial Neural Network (ANN)

Table 2: Production planning data of mobile phone (sixth generation) released to market last year.

Events	Week	Pr. Quantity (FG.)	Stocks (FG.)	Inventory Level (FG.)	Pr. Quantity (WIP.)	Stocks (WIP.)
Start WIP.	40	0	0	0	34,000	34,000
	41	0	0	0	34,000	68,000
	42	0	0	0	34,000	102,000
	43	0	0	0	34,000	136,000
Start FG.	44	42,000	42,000	42,000	34,000	128,000
	45	42,000	84,000	84,000	34,000	120,000
	46	42,000	126,000	126,000	34,000	112,000
	47	42,000	168,000	168,000	34,000	104,000
	48	42,000	210,000	210,000	34,000	96,000
	49	42,000	252,000	252,000	34,000	88,000
Release FG.	50	42,000	56,550	56,550	34,000	80,000
	51	42,000	0	-78,890	34,000	72,000
	52	42,000	0	-149,006	34,000	64,000
	1	42,000	0	-170,889	34,000	56,000
	2	42,000	0	-157,503	34,000	48,000
	3	42,000	0	-136,076	34,000	40,000
	4	42,000	0	-110,484	34,000	32,000
	5	42,000	0	-78,034	34,000	24,000
	6	32,000	0	-52,595	34,000	26,000
	7	30,000	0	-26,754	34,000	30,000
	8	28,000	0	-1,862	34,000	36,000
	9	28,000	23,368	23,368	34,000	42,000

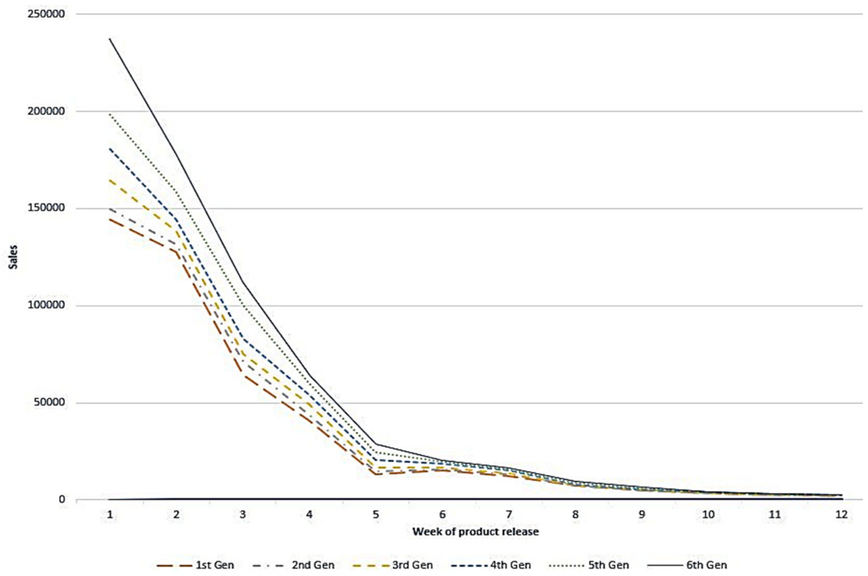

Figure 1: Historical weekly sales data for past mobile phone generation.

We visualize the historical demand data, as shown in Figure 1 which illustrates historical data from the past 6 years mobile phone generation. Obviously, sales will be the most in the first week of product release, after which there will be a significant decrease in sales from weeks 1-6. From week six onwards, sales fell in steady volumes to the lowest sales in week twelve.

Then, we divide the training data set to be demand data from year 1(first gen) to year 5 (fifth gen). For the testing data set we use the demand data for year 6 (sixth gen). We measure the accuracy of the forecasting method by using MAD, RMSE, and MAPE evaluation as following equations.

$$MAD = \sum_{t=1}^{n} \frac{|D_t - F_t|}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(D_t - F_t)^2}{n}} \quad (2)$$

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|D_t - F_t|}{D_t} \quad (3)$$

Noted that, to determine appropriate parameters for each forecasting model, we implemented Time series package in R software.

The next step after obtaining the suitable forecasting. According to the case study company's problem survey, we found that there is still a lack of placement to link among inventory quantities, demand forecasts, and production rates, whether finished goods (FG.) or work in process (WIP.). Therefore, it is necessary to establish this link to manage inventory efficiently. We summarize the linking steps as follows.

Step: 1 Calculate the number of weeks to stock FG. and WIP. for peak demand using equation (4).

Step 2: Make production planning of FG. and WIP. in accordance with demand and inventory levels, as shown in Table 5.

$$n = \frac{\sum_{w=1}^{k+1} F_w}{Cap_{fg/wip}} \quad (4)$$

where n = number of weeks required to stock FG. and WIP.

F_w = The forecast amount of demand that exceeds capacity.

w = weeks in which the forecast demand exceeds capacity.

k = number of weeks where demand exceeds capacity.

Lastly, we conduct costs comparison between proposed scenario versus that of problem scenario based on two costs components as approximated loss sales and inventory carrying costs.

5 RESULTS

As previously mentioned, we preliminary select forecasting methods that are suitable for this problem. These are (1) Holt-Winters' Seasonal Method (HW.), (2) Autoregressive Integrated Moving Average (ARIMA), (3) Exponential Smoothing (ETS.), and (4) Artificial Neural Network (ANN.).

For various forecasting methods, it is necessary to identify appropriate parameters to make the most accurate forecasts. We summarize these parameters for each forecast method as follows.

- HW forecasting showed that the optimal parameters with the least forecast error were multiplicative, with smoothing coefficients of α = 0.0463, β=0.0443, and γ=0.8344.
- For ARIMA models, the appropriate parameters that cause the least tolerances are: ARIMA (0,0,1) (1,1,1) [12] with drift.
- The Exponential Smoothing (ETS) forecast method found that optimal parameters were α = 0.0242, β=0.0242, and γ=0.9758.
- The last method, the Neural Network (ANN) method, found that the ideal model was NNAR (2,1,2) [12] that was seasonal, and lagged 1, 2, and 12 (y_{t-1}.,,y_{t-2}.,,y_{t-12}.) of each season were inputs, with 2 Neurons in the Hidden Layer.

Table 3: Forecast errors for training dataset (gen1-gen5).

Method	HW.	ARIMA	ETS.	ANN.
MAD	1,202.20	1,280.54	1,210.91	949.97
RMSE	2,147.60	2,180.47	2,354.12	1427.46
MAPE	4.89	7.84	2.99	5.41

As shown in Table 3, ANN. method provides the smallest forecast errors for MAD. and RMSE. cases, while ETS. provides the smallest error in MAPE. As mentioned in (Vandeput, 2021), selecting the suitable demand forecast method based on using MAPE., the forecast value is often lower than it should be. While using RMSE., the forecast value is about the average value. On the other hand, MAD. often gives higher forecast value than it should be. Therefore, in this research, we prefer average forecast value, so RMSE. seems appropriate. Therefore, we select the right forecasting method based on RMSE., where the best forecast method in this case is ANN.

For testing data set, by using the ANN method, we forecast demand of sixth generation mobile phone and compare it with the original forecast method, see Table 4 for the ANN. forecast results. From that table, it shows that forecast values obtained by ANN method are more accurate than those of the original forecast. The original method has forecast error based on calculated MAD, RMSE, and MAPE as 7972.17, 12410.48, and 16.46, respectively. While proposing ANN has MAD = 3030.044, RMSE = 6046.08, and MAPE = 5.41, respectively. In other words, ANN is 51.28% more accurate than the original forecast method based on RMSE.

Table 4: Forecast results comparison for gen sixth model.

Week	Demand	Old Forecast	New Forecast (ANN.)
1	237,450	210,000	219,496
2	177,440	150,000	174,983
3	112,116	100,000	122,044
4	63,883	75,000	67,042
5	28,614	26,000	28,560
6	20,573	15,000	21,117
7	16,408	11,000	15,413
8	9,550	8,500	8,988
9	6,561	5,000	6,431
10	4,159	3,500	4,325
11	3,108	2,600	3,322
12	2,770	2,600	2,968

Then, we calculate number of weeks to stock FG. and WIP. using equation (4). WIP. should start at week thirty-seven while FG. should start at week forty-two, respectively. Additionally, the capacity should increase from 42,000 to 50,000 units. The proposed production planning for solution scenario of sixth generation mobile phone is conducted and shown in Table 5.

6 SUMMARY AND DISCUSSION

In this paper, we found the major problem which is inaccurate demand forecast that causes mis planning of both FG. and WIP inventory volumes. Therefore, we present the better forecast method based on ANN, which gives 51.28% more accurate than that of the original method. Then, we develop the proposed solution plan that links together inventory quantities, demand forecasts, and production rates, for both finished goods and work in process.

We then compare the proposed solution scenario with the problem scenario based on two cost components as approximated loss sales and inventory carrying costs. By knowing the sales margin, in this case $155.00, we calculate the total sales loss value of the problem scenario as $3,085,070.00, where the proposed solution scenario has zero loss sales cost (no backlog).

For the inventory carrying cost based on weekly carrying cost for WIP inventory/unit =$0.53, and weekly carrying cost for FG inventory/unit = $1.20, we calculate inventory carrying cost for problem scenario as $1,969,441.60 and that of solution

Table 5: Production planning for solution scenario of sixth generation mobile phone.

Events	Week	Pr. Quantity (FG.)	Stocks (FG.)	Pr. Quantity (WIP.)	Stocks (WIP.)
Start WIP.	37	0	0	37,500	37,500
	38	0	0	37,500	75,000
	39	0	0	37,500	112,500
	40	0	0	37,500	150,000
Start FG.	41	0	0	37,500	187,500
	42	50,000	50,000	37,500	175,000
	43	50,000	100,000	37,500	162,500
	44	50,000	150,000	37,500	150,000
	45	50,000	200,000	37,500	137,500
	46	50,000	250,000	37,500	125,000
	47	50,000	300,000	37,500	112,500
	48	50,000	350,000	37,500	100,000
	49	50,000	400,000	37,500	87,500
Release FG.	50	50,000	215,000	37,500	75,000
	51	50,000	90,000	37,500	62,500
	52	50,000	30,000	37,500	50,000
	1	50,000	18,000	37,500	37,500
	2	27,061	18,061	0	10,439
	3	10,439	9,500	18,944	18,944
	4	14,974	9,474	0	3,970
	5	3,970	4,944	8,237	8,237
	6	5,409	4,853	0	2,828
	7	2,828	4,181	3,423	3,423
	8	2,355	4,086	0	1,068
	9	1,068	2,604	2,462	2,462

scenario as $3,653,885.23. Therefore, summing loss sales and carrying costs together we obtain the total cost for problem and solution scenario as $5,054,512.03 and $3,653,885.23, respectively. On the other hand, upon implementing solution scenario, we can reduce costs by $1,400,626.80 or by 27.71%.

Somehow, in this research, we propose the solution scenario on forecasting only product demand without considering other important variables such as promotion and competitors. Therefore, for future research, it would be more practical if we included these variables into building the forecast model.

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