# Comparison of Time Series Models for Forecasting Sales in Multi Level Marketing (MLM) Business

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## Abstract

This study aims to analyze and compare the performance of time series models in forecasting sales for network marketing businesses. Traditional models such as ARIMA are compared with modern models like Facebook Prophet. The study uses actual monthly sales data from network marketers, covering the period from January 2025 to February 2025, totaling 1.5 months. The performance of the models is evaluated using statistical metrics including RMSE, MAE, MAPE, and $R^2$ Score. The results reveal that ARIMA tends to provide more accurate forecasts than Facebook Prophet. This research is important for the network marketing sector, as accurate sales forecasting enables entrepreneurs to effectively plan marketing strategies and manage inventory. Furthermore, comparing the effectiveness of time series models supports business owners in selecting suitable tools to analyze sales trends and business growth.

However, the research is still in the experimental phase, and results may change as more diverse data becomes available.
***Keywords:*** Sales Forecasting, Time Series, ARIMA, Facebook Prophet

## Background and Statement of the Problem

Network marketing plays a significant role in both the Thai and global economies by utilizing a network of independent business owners to distribute products and services. Sales forecasting is a critical factor that enables network marketers to plan marketing strategies and make informed business decisions effectively (Somsiri, 2023). Accurate forecasting helps reduce the risks of product shortages or overstocking, which directly impact business costs and profitability. In Thailand, for example, the network marketing industry was valued at approximately 60 billion baht in 2023 (ThanKhao Today, 2024). Globally, the multi-level marketing (MLM) market was worth USD 201 billion in 2022 and is expected to continue growing (Zion Market Research, 2023), reflecting the significance of network marketing within the economic system. Therefore, studying sales forecasting is essential for enabling businesses to plan strategies with greater accuracy and efficiency. We found that traditional models like ARIMA offer reliable trend handling and have a strong foundation in academic research, making them suitable for structured sales data. Inspired by Zhang's (2003) work, we chose ARIMA as one of the models for our comparative analysis.

Time series models are widely used techniques for forecasting data, such as monthly sales (Cheansunan, 2023). ARIMA is recognized as a classic model due to its strong capability in handling data trends, especially when the data exhibits a clear structure (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018). The research by (Kim, Y., Kim, S., & Shin, D. 2019) suggests that ARIMA remains an effective baseline model, especially when combined with in-depth models, to increase the accuracy of forecasting promising data. Meanwhile, Facebook Prophet is a modern model capable of automatically managing changing trends and irregular seasonality (Chikkakrishna et al., 2022). One of Prophet's key advantages is its flexibility in incorporating external regressors to improve forecasting accuracy. Therefore, this study selects both ARIMA and Facebook Prophet to compare their performance in forecasting network marketing sales. ARIMA is suitable for data with clear structural trends, while Prophet supports more complex and frequently changing patterns (Chanthes, 2023).

This study therefore focuses on comparing the efficiency of the historical time series model with the current time series model in forecasting sales of direct selling business operators by using actual sales data from the network business operators' companies. This study aims to help entrepreneurs select and apply the most appropriate model for sales forecasting, which will affect business strategy planning and increase efficiency in inventory management. It is also useful for researchers and those interested in developing an efficient sales forecasting system using a time series model.

**Objective**

1. To analyze and compare time series forecasting models, specifically ARIMA and Facebook Prophet.
2. To predict the sales performance of network marketers using statistical indicators such as RMSE, MAE, MAPE and $R^2$ Score.

**Expected Benefits**

1. To understand the characteristics of the data that are suitable for each model and to be able to select the model that is appropriate for the data characteristics of the network business.
2. To provide network entrepreneurs with tools to help them forecast sales and improve their business efficiency.

**Conceptual Framework**

This research is based on the concept of Time Series Forecasting, which involves analyzing data recorded over time to predict future values (Box & Jenkins,1976). The study applies both traditional and modern forecasting techniques to compare their efficiency in predicting the business performance of multilevel marketing.

The conceptual framework shown in Figure 1 serves as an important guide for conducting this research. It begins with Input (data and contributing factors) → Process (analytical procedures) → Output (results), forming a structure that improves the accuracy of sales forecasting for multilevel marketing companies and supports effective strategic business planning.

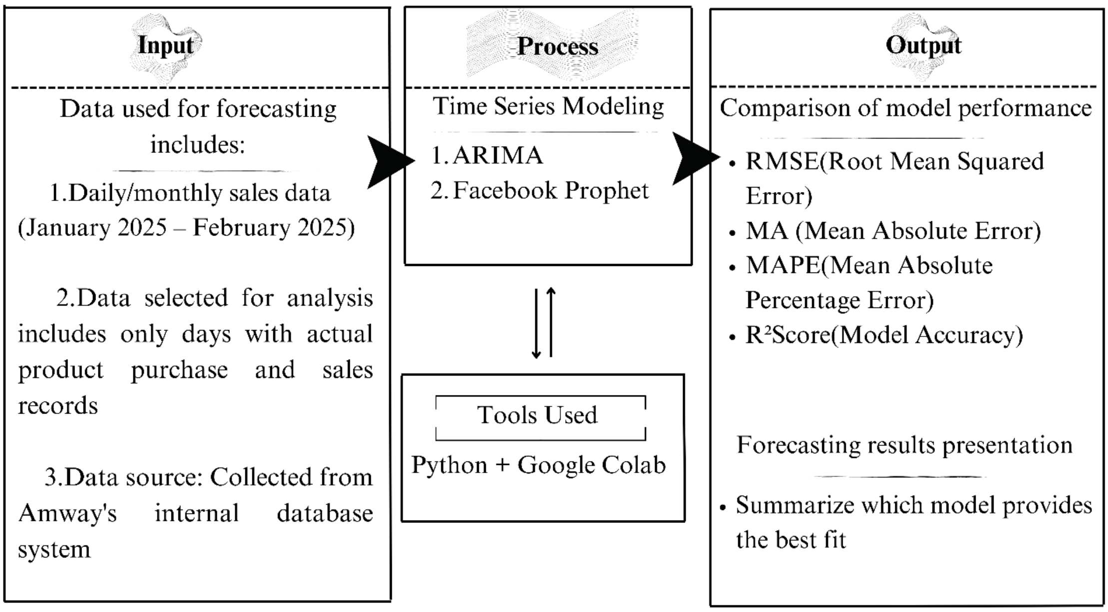


Figure 1 Illustration of the conceptual framework

**Concepts of traditional time series models**

ARIMA (Auto Regressive Integrated Moving Average) is a statistical model used to identify trends in time series data and is particularly effective when the data does not exhibit strong seasonal patterns (Box & Jenkins, 1976). It builds forecasts by utilizing past values and their errors, making it suitable for short-term forecasting.

The ARIMA model consists of three main components:

1. AutoRegressive (AR): Utilizes past observations to predict future values. The parameter *p* indicates how many lagged observations are included.
2. Moving Average (MA): Uses past forecast errors in a regression-like model. The parameter *q* indicates the number of lagged forecast errors.
3. Integrated (I): Involves differencing the raw observations to make the time series stationary. The parameter *d* indicates the number of differences needed.

The general form of the ARIMA model is expressed as ARIMA (p, d, q), where:

*p* = order of the autoregressive part
*d* = degree of first differencing
*q* = order of the moving average part

If $q = 0$, the model simplifies to AR(p), and if $p = 0$, it becomes MA(q)

The ARIMA (1) model can be represented by the following linear equation:

$$y_t = \delta + \emptyset_1 y_{t-1} + \dots + \emptyset_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \qquad (1)$$

Where:

$y_t$ is the observed value at time *t*
$\delta$ is a constant term in the model
$\varepsilon_t$ is the random error term at time *t*, which is assumed to be independently distributed with a constant mean and variance
$\emptyset_i$ $( i = 1, \dots, p )$ and $\theta_j$ $( j = 1, \dots, q )$ are the parameters of the model, where p and q are integers that represent the order of the model p and q

**Concepts of modern time series models**

Facebook Prophet is a forecasting model developed by Facebook that is designed to be easy to use and can handle trend data and seasonal components well (Hyndman & Athanasopoulos, 2018). The Facebook Prophet equation uses a Generalized Additive Model (GAM) where the forecast $y(t)y(t)$ is defined as the sum of three principal components and equation (2) is as follows:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \qquad (2)$$

Where:

*g(t)* is the trend function (linear or piecewise linear)
*s(t)* is the seasonality function, modeled using Fourier series
*h(t)* is the function that uses the holiday impact model
$\varepsilon_t$ is the error term assumed to be normally distributed, $N(0, \sigma^2)$

Trend Equations

Facebook Prophet supports both linear and piecewise linear trend modeling:

Linear Trend Equation (3):

$$g(t) = (k + a(t)\delta)t + b \qquad (3)$$

Piecewise Linear Trend Equation (4):

$$g(t) = kt + \sum a_j(t)\delta_j \qquad (4)$$

Where:

*k* is the initial growth rate
$a_j(t)$ is an indicator function that determines the changepoint of the trend
$\delta_j$ is the change in slope at that inflection point
*b* is the offset parameter of the trend

**Concept of Model Evaluation**

The performance of the model was evaluated using statistical metrics, including the $R^2$ (coefficient of determination) score, which measures the accuracy of the model in explaining the variability in the observed data. It is a commonly used metric to assess the goodness of fit of regression models. The $R^2$ score is calculated using equation (5) as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \widehat{y_i})}{\sum_{i=1}^{N}(y_i - \bar{y}_i)} \qquad (5)$$

Where:

$y_i$ = Actual value of observation i
$\widehat{y_i}$ = Predicted value of observation i
$\bar{y}$ = Mean of the observed values
$N$ = Number of observations

Root Mean Square Error (RMSE) (Hodson, 2022) is a metric used to evaluate the accuracy of a forecast or prediction model. It measures the average size of the difference between the predicted and actual values by calculating the square root of the mean squared difference. The RMSE value represents the overall error between the predicted and actual values, with lower values indicating higher accuracy. The RMSE is commonly used in various fields such as statistics, machine learning, and time series analysis to evaluate the performance of models and compare different forecasting methods. It can be calculated according to equation (6) as follows:

$$\text{RSME} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})} \qquad (6)$$

MAE (Mean Absolute Error) (Hodson, 2022) is the mean absolute error calculated by calculating the average error of the predicted value with the actual value. The error in MAE is calculated in terms of absolute values, so there is no need to worry about positive or negative values. This means that MAE simply reflects the average error of the model, which can be calculated according to equation (7) as follows.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i) \qquad (7)$$

The Mean Absolute Percentage Error (MAPE) (Wang, X., Smith, K. A., & Hyndman, R. J. 2020) is a measure of the accuracy of a predictive model by calculating the prediction error as a percentage of the true value, allowing the comparison of model accuracy with data of different scales. MAPE is an appropriate measure for comparing the accuracy of models that predict data of different sizes. However, it should be used in conjunction with other measures such as RMSE and MAE for a more comprehensive analysis, which can be calculated using equation (8) as follows.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \hat{y}_i}{y_i}\right)x100 \qquad (8)$$

**Research Methodology**

1. Collect sales data of network entrepreneurs using monthly sales data from the company's database from January 2025 to February 2025, a total of 1.5 months. The data used includes business ID, name, transaction date, order details, and sales. However, only transaction date and sales are used in the sales forecast because they reflect the trend of the data over time.
2. Clean and prepare the data by managing missing values, adjusting date formats, and converting the data to a format suitable for time series forecasting.
3. Develop a sales forecasting model using the ARIMA and Facebook Prophet models using Python and Google Colab tools, dividing the data into a training set and a test set.
4. Perform sales forecasting by using each model to predict sales in advance, analyze the predicted sales trends, and compare the results.
5. Evaluate the performance of the model. By using the RMSE, MAE, MAPE and $R^2$ Score indicators, which are criteria used to measure the accuracy of the prediction. RMSE and MAE are used to measure the error value of the model. MAPE is used to evaluate the percentage error. And $R^2$ Score is used to evaluate the ability of the model to explain the trend of the data.

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6. Analyze the results and summarize the research findings. By presenting a comparison of the performance of different models. Along with showing the trend of predicted sales. And conclude which model is the most accurate and appropriate for forecasting sales of network businesses. And to add factors or find other models in future experiments.

**Research Results**

This research focuses on comparing the performance of traditional time series models and modern time series models. First, ARIMA and Facebook Prophet were experimented to forecast the sales of direct selling companies using 156 rows of data (about 1.5 months) and analyzed using RMSE, MAE, MAPE, and $R^2$ Score indicators. Table 1 shows the basic statistics of the data set used in the experiment. The data shows that there is a lot of fluctuation in sales on a daily basis, which may affect the accuracy of the prediction.

**Table 1** Basic Statistics of Network Business Sales Data

| Variable | Maximum | Minimum | Mean | Standard Deviation |
|---|---|---|---|---|
| Sales | 42718 | 11 | 2905.98 | 5626.46 |

The change in sales can be seen from the graph in Figure 2, which shows the fluctuation of the data, which clearly shows the trend of daily sales over a period of one and a half months, with some periods of significant sales spikes, which may be due to external factors such as promotions or periods of increased demand for the product.

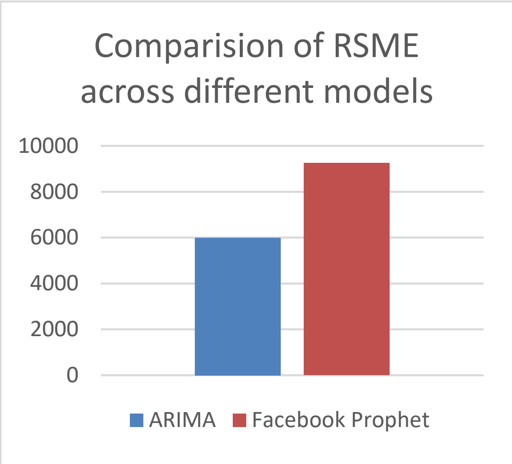

Figure 2 Graph showing the volatility of the data

And the results of Table 2 show the efficiency of the model used. ARIMA has a RMSE value of 5,982.42 and MAE of 2,961.8, which is lower than Facebook Prophet's RMSE value of 9,248.3 and MAE of 8,033.9, showing that ARIMA has a lower mean error. However, MAPE has a problem with dividing by zero, resulting in inf% and negative $R^2$ values in both models. ARIMA has a value of -0.0023 and Facebook Prophet has a value of -1.3952, reflecting that the model is still unable to explain the trend of the data well.

**Table 2** Results of ARIMA & Facebook Prophet Model

| Model | RMSE | MAE | MAPE (%) | $R^2$ Score |
|---|---|---|---|---|
| ARIMA | 5982.42 | 2961.8 | inf% | -0.0023 |
| Facebook Prophet | 9248.3 | 8033.9 | inf% | -1.3952 |

When comparing the average absolute error and the square root of the average absolute error of each model in a graph, the differences are clearly seen, as shown in Figure 3.



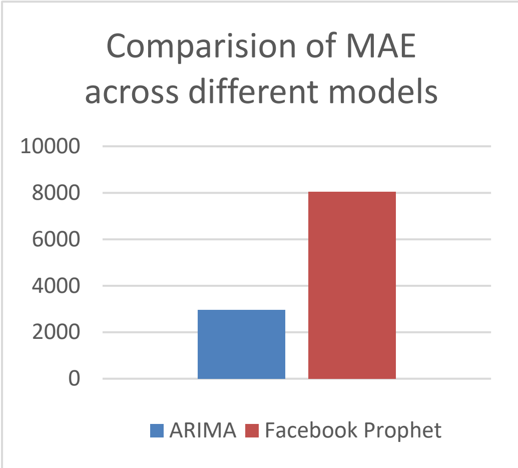




Figure 3 shows a graph comparing the values of the mean absolute error and the square root of the mean absolute error.

When comparing the mean error (MAE) and root mean square error (RMSE) of each model in a graph, it is clear that ARIMA has a significantly lower error than Facebook Prophet. The experimental results show that the ARIMA model performs better than Facebook Prophet in forecasting sales of network entrepreneurs, considering the significantly lower RMSE and MAE values, which reflects higher accuracy in forecasting this data set. However, the negative $R^2$ Score in both models also indicates that the models are not able to explain the trends of the data well, which may be due to the limited amount of data or the high volatility in daily sales. Additionally, the MAPE value appears as "inf%" (infinity percentage), which typically occurs when actual sales values are zero or near zero in some instances, making percentage-based error calculations mathematically undefined or infinitely large. The results of the study can be used as a guideline for developing a more accurate forecasting model by adjusting the model parameters to be more suitable or experimenting with other Machine Learning techniques such as NeuralPhopet, XGBoost or LSTM to increase the efficiency of future forecasting.

**Summary of the Study**

This research studies the efficiency of time series models in forecasting sales of network entrepreneurs using 156 rows of monthly sales data and analyzed via Python and Google Colab. The results show that ARIMA has higher accuracy than Facebook Prophet, but the model still has limitations in explaining data trends.

In the future, environmental factors such as seasonality and promotions should be added and advanced machine learning should be tested to increase forecast accuracy.

**Discussions**

The research findings reveal that ARIMA outperforms Facebook Prophet in forecasting sales of network marketing businesses. This is consistent with Box and Jenkins (1976), who noted that ARIMA is well-suited for time series data with clear trends and no complex seasonal patterns. In contrast, Facebook Prophet is designed to handle more complex data and did not perform optimally in this study, likely due to the limited dataset used. Specifically, only 1.5 months of data (156 rows) were available, which may be insufficient for models that require a larger dataset to effectively learn trends (Hyndman & Athanasopoulos, 2018).

These findings are further supported by Chanhan (2022), who reported that ARIMA demonstrated high accuracy in forecasting Bitcoin prices—a dataset with relatively consistent trends—reinforcing ARIMA's suitability for data with similar characteristics. Meanwhile, Chanthes (2023) found that Prophet produced more accurate forecasts when applied to datasets with additional contextual variables such as seasonality and holidays. This supports the present study's suggestion that Prophet may perform better when such external factors are included in the dataset.

Additionally, Kim, Kim, and Shin (2019) proposed hybrid models that integrate ARIMA with Deep Learning techniques, particularly Long Short-Term Memory (LSTM). LSTM is a type of recurrent neural network capable of retaining memory over long sequences, making it especially suitable for time series data with high uncertainty. This suggests a promising direction for future research, which could explore the development of hybrid models to improve predictive performance. In the same vein, Gamboa (2017) emphasized the potential of Deep Learning for modeling complex and rapidly changing time series data, further supporting the idea of model enhancement through advanced techniques.

While ARIMA delivered better results in this study, it is important to acknowledge the limitations of the dataset—namely, the short time span and lack of supporting variables like promotions or seasonal indicators. These limitations may have impacted the overall predictive accuracy. Expanding the dataset to include a longer time frame and incorporating additional relevant factors could improve the performance of other models, especially those based on Machine Learning.

Finally, it is recommended that the research findings be tested in real business environments, particularly with network marketing entrepreneurs. Doing so would allow for assessment of the models' applicability and effectiveness under practical conditions, and could help refine the models for greater business value.

## Recommendations

To improve the accuracy of the forecast, it is advisable to increase the model training data, perhaps by collecting data covering longer time periods, such as 6 months or 1 year, and experimenting with other machine learning models such as NeuralPhopet, XGBoost, or LSTM, which have the ability to learn complex patterns of data. In addition, using Auto ARIMA and Hyperparameter Tuning for Facebook Prophet may help to obtain more suitable parameter values. In the future, sales forecasting should be studied by incorporating additional factors such as promotions, seasonality, and customer behavior to enhance the efficiency of the forecasting model. And recommends that network businesses to experiment with the ARIMA model on their sales data to plan effective stock management and promotions. Meanwhile, multi level marketing companies can use this research to choose the right model for their data. To support strategic decision making.

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