Implementation of Time Series Forecasting Using Single Moving Average Model - A Case Study in Printing Industry

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Abstract

The first step in optimizing the overall planning process is to develop a reliable forecasting process. In this paper we discuss the implementation of forecasting in the printing industry, forecasting the timing of demands is one of the critical issues. Time series is a collection of observations made at regular time intervals and its analysis refers to problems in correlations among successive observations. A Simple Moving Average model is a time series constructed by taking averages of several sequential values of another time series. To support the research, data collection from the firm is needed. In order to find the best model, the research will be supported by graphic visualization, analysis, and the accuracy of the Single Moving Average model for demand forecasting with data obtained from the firm over the course of 1-2 years. The demand products are provided by CV. Mitrakom Bintang Kemilau firm. In this paper we calculated 3 different data, two of the three are based on the types of product which have the most sales percentage within 2 years of production, shelf talker and wobbler, the other is total products produced by the firm. Based on the three types of data we gathered two years in advance, we found evidence that forecasting data using the Single Moving Averages model results in 30%-50% errors using the error standard of Mean Absolute Percentage Error (MAPE) supported by Mean Absolute Deviation (MAD) and Mean Squared Error (MSE).

Keywords
Forecasting, Single moving average, Accuracy, Printing industry, MAPE

1. Introduction
Demand forecasting helps companies make choices about how many goods they can manufacture in the future. Good forecasts should provide useful information to help with decision-making (Murphy 1993), and they should be reliable enough that different forecasts will not affect the decision (Voulgaris 2019). The two main causes of quantifiable uncertainty in travel demand forecasts are: model inputs and the models themselves in their specification and parameters (Hugosson 2005). Forecasters can combine either approach with Monte Carlo simulation, which uses a probability distribution of the input variables and constructs a distribution of outputs (Lemp and Kockelman 2009; Aldrete et al. 2010; de Jong et al. 2007; Manzo, Nielsen, and Prato 2015a, 2015b). Others are exploring ways to efficiently define the scenarios to run (Knaap et al. 2020).

The printing firm, CV. Mitrakom Bintang Kemilau, produces many products to their customers based on the orders. The firm uses MTO (make to order) standard policy. In a make-to-order environment, manufacturers usually wait until an order is received from a customer before starting to make the goods. Based on the products sold by the CV. Mitrakom Bintang Kemilau, we can see that some of the products are seasonal and in trend, others are in random variations. Other characteristics are the customer usually willing to wait while the order is being made and the products are quite rare to find in the market. The customers of these products are dominated by convenience stores from Indonesia such as Alfamart, Alfamidi, and Lawson. The place of this production and its customers are limited around JABODETABEK (Jakarta, Bogor, Depok, Tangerang, and Bekasi) and not all convenience stores included in those areas are buying from the same supplier.

While personnel scheduling optimization by using an approach of mathematical model is capable of providing optimal personnel scheduling, reduces the amount of manpower delays and can be used to analyze the needs of labor based on the number of existing projects (Nurcahyo et al. 2009), there hasn't been any methods of scheduling used by the this firm for the work optimization. Thus, this research paper addresses the application of Time Series Forecasting using Single Moving Average Model concepts to the printing industry. CV Mitrakom Bintang located in Jl. Cawang Baru Barat No. 23, East Jakarta.

1.1 Problem Statement

Forecasting has been widely used to predict orders that a company will receive in order to prepare series. This is usually done so that companies can reduce production costs for possible excess products or other procedures. Printing companies tend to use a made-to-order system so that in preparation the company can fail to estimate the number of orders that might be obtained.

1.2 Objective

Time series analysis includes autoregressive and moving average processes and the correlations of some statistical inference. The application of time series in this paper specifically moving averages model is to describe and summarize time sets of data. These are two primary objectives of this study:

a) To analyse and track forecast from the error that will result in determining how good a forecast is based on the historical data
b) To determine the implementation of demand forecasting using simple moving average methods that can be done in the printing industry.

2. Literature Review

2.1 Time Series Model

Before any methods can be used in any forecasting, it must be ensured that the applicability and reliability are suitable for the application of the situations. A time series is a sequence of observations taken sequentially in time. Many data sets on the industry are by definition time-series (e.g., yearly orders in a factory for clothing, weekly series of sales, or hourly observations of manufacturing goods) (Seifert et al. 2015). The main aim of time series modeling is to carefully collect and rigorously study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This model is then used to generate future values for the series, i.e. to make forecasts.

One of the most popular and frequently used stochastic time series models is the Autoregressive Integrated Moving Average (ARIMA) model. The basic assumption made to implement this model is that the considered time series is linear and follows a particular known statistical distribution, such as the normal distribution. The ARIMA model has subclasses of other models, such as the Autoregressive (AR), Moving Average (MA) and Autoregressive Moving Average (ARMA) models. These methods can be easy to use, such as using the most recent observation as a forecast (naïve method), or exceedingly complex, such as neural networks predictions. The best model to use depends on several factors such as; historical data, the connections between the forecasting attribute with the predictors, time horizons, and implementations. However, there are some limitations of these models, the pre-assumes linear form of the associated time series becomes inadequate in several practical situations (Andhikari et al. 2013).

The general tendency of a time series to increase, decrease or stagnate over a long period of time is termed as Secular Trend or simply Trend. Thus, it can be said that trend is a long term movement in a time series. Seasonal variations in a time series are fluctuations within a year during the season. The important factors causing seasonal variations are: climate and weather conditions, customs, traditional habits, etc. The cyclical variation in a time series describes the medium-term changes in the series, caused by circumstances, which repeat in cycles. The duration of a cycle extends over a longer period of time, usually two or more years. Irregular or random variations in a time series are caused by unpredictable influences, which are not regular and also do not repeat in a particular pattern. These variations are caused by incidences such as war, strike, earthquake, flood, revolution, etc.

2.2 Simple Moving Average

In this paper, we used the MA (Moving Average) model with a single used method or SMA(Single Moving Average).In this method we generate subsets and find out means of the subsets and plot them to find out the movement of the line segment generated by connecting points plotted at averages. But the subset must have minimum values to find mean. As data from a new time period is added, data from an earlier time period is dropped from the average calculation. The simple statistical method of moving averages may mimic some data better than a complicated mathematical function. Moving averages are also useful to filter out random fluctuations. This has some common sense since periods of high demand are often followed by periods of low demand.
The general equations for simple moving average is as follows:

$$SMA = \frac{v_x + v_{x-1} + \ldots + v_{x-(n-1)}}{n} \ldots (i)$$

Where, $v_x = Value\ for\ metric\ x$
$n = no.of\ spans\ in\ subset.$

2.3 Measurement of Forecasting Error

One of the most important tasks in determining forecasting is improving forecast accuracy. Forecast accuracy has a major impact on business costs and profit. Forecasting process must be evaluated by individual and aggregated forecast-accuracy metrics. Tracking these metrics over time is critical to driving process improvement (*How to Track Forecast Accuracy to Guide Forecast Process Improvement*, 2009).

2.3.1 Mean Absolute Deviation (MAD)

A common method for measuring overall forecast error is the mean absolute deviation. Heifer and Render (2001) noted that this value is computed by dividing the sum of the absolute values of the individual forecast error by the sample size (the number of forecast periods). The equation is:

$$\text{MAD} = \frac{1}{n} \sum_{n=1}^{n} |(\text{Actual} - \text{Forecast})|$$

2.3.2 Mean Squared Error (MSE)

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. Jarrett (1991) stated that the mean square error (MSE) is a generally accepted technique for evaluating exponential smoothing and other methods. The equation is:

$$\text{MSE} = \frac{\sum_{k=0}^{n} \{\text{Actual} - \text{Forecast}\}^2}{n}$$

n = the number of periods (Lemke, 2000, 67-110)

2.3.3 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) Mean Absolute Percent Error (MAPE) is the most common measure of forecast error. MAPE functions best when there are no extremes to the data (including zero). With zero or near-zero, MAPE can give a distorted picture of error. The error on a near-zero item can be infinitely high, causing a distortion to the overall error rate when it is averaged in. For forecasts of items that are near or at zero volume, Symmetric Mean Absolute Percent Error (SMAPE) is a better measure (Ivakhenko, 1970, 219) . MAPE is the average absolute percent error for each time period or forecast minus actuals divided by actual:

$$\text{MAPE} = \frac{1}{n} \sum_{n=1}^{n} \frac{|\text{Actual} - \text{Forecast}|}{\text{Actual}} * 100\%$$

3.1 Methods of Producing Printing Products

On CV. Mitrakom Bintang Kemilau, printing process is divided into prepress, press, and postpress steps.

3.1.1 Prepress

Operations encompass steps during which the idea for a printed image is converted into an image carrier such as a plate, cylinder, or screen. The design process at CV Mitrakom Bintang Kemilau uses Corel Draw software to process vector files and Adobe Photoshop to process image files.

- Design

The design process starts with determining the size of the product to be printed. Then continued with the creation of the design in accordance with the specifications desired by the customer. In the design process, it is necessary to pay attention to the prepared files that are whether the image is optimal so that it does not break when printed. It is necessary to check the completeness of the file to be printed so that no image is left behind. Also check the texts on the design so that there is no writing error.

- Printing plate manufacturing

The printing plate in the offset print process is used as a print reference that moves the image to the print media. The process of making a print plate can be done using two methods, namely by making the plate manually and by using CtP / CtCP.

3.1.2 Press

The printing process serves to duplicate a set of images or text according to the print/plate reference made in the previous pre press section. In this multiplication process, the parameters that must be considered include the accuracy of the register, the accuracy of a color, cleanliness of the printout, stability of the paper, etc. The offset printing process is an indirect print, meaning the ink switching of the print reference is not directly about the print material, but through the medium of 40 intermediaries namely rubber cylinders (blanket cylinders). The position of the image of the printed reference is readable, then on the blanket cylinder is unreadable and reaches the readable print material. The principle of offset printing can be described in the print process scheme below

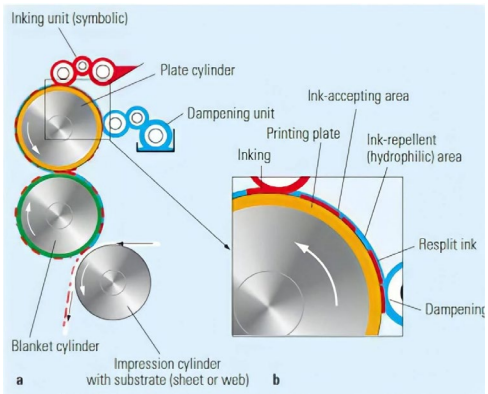

Figure 1. Offset Printing Process

At CV Mitrakom Bintang Kemilau, offset machines are used using stream feeder systems. The system consists of several components.

1. Paper stacking table, which serves to put to be printed.
2. The suction head consists of: Paper height touch shoes equipped with air blower, paper separator plate, paper separator blowing rod, lift suction, transport/successor suction, transport suction cranks.
3. Delivery table, which serves to deliver the paper taken by the suction head group to be taken to the printing unit. On this delivery table, there are several tools including transportation tires, delivery wheels, retaining brush wheels, side lay, front lay.
4. Double sheet detector, which serves to detect when there is double-sucked paper. This tool is set to pass 3 sheets of paper and keep running and 4 sheets of paper transport unit stops.

Figure 2. Line System Stream Feeder

3.1.3 Postpress

Primarily involves the assembly of printed materials and consists of binding and finishing operations.

3.2 Study Procedure

This study uses a primary data set for conducting the experiment. Data for this research were gathered and structured from raw data sales per month for two years from 2019 to 2020. These data were collected with legal approach with permission from the owner of the firm. The study focused on products that are not included in random variations, means the products that are produced repeatedly for months in two years. The data of products that are produced most of the months were gathered and analyzed in this paper.

4. Data Collection

These are collected data sales that are already sorted based on the types of the products that are repeatedly produced for the past two years from 2019 to 2020. Hence the study focused on 10 main products, which are flyer, header, pop, price card, hanging, shelftalker, selftrip, poster, wobbler, and brandliner. Table 1 shows the sales for 10 main products in 2 years per month in CV. Mitrakom Bintang Kemilau firm.

Table 1. Monthly data for product sales in CV. Mitrakom Bintang Kemilau

Year	Month	Flyer	Header	Pop	Price card	Hanging	Shelftalker	Selftrip	Poster	Wobbler	Brandliner
2019	1	18000	1508	15009	828	57706	4999463	7540	47214	2538818	
	2	9000	15708	796667	779	79367	6842336	3024	33478	2484479	7500
	3	22000	1574	31654	436	100239	5877464	6430	37285	3442119	24523
	4	14000	5033	40034		91033	3634477	4575	3272	4015664	32943
	5	8000	13995	26001	50	74927	10228490	800	31202	3750830	
	6			23019	96	95885	3693410	3098	25571	1525607	8278
	7	12000	1624	29685	80	106387	7915047	3076	30399	3147605	28278
	8	12000	12235	27852	465	67961	8781946	7800	21137	4652719	
	9	45500	17180	13951	220	110314	8468478	7537	33091	3262947	71695
	10	49100		40553	400	66641	7932502	3176	15866	3465842	
	11	53200	200	19003	60	80996	11369509	6333	47385	8369724	10200
	12	49000	20239	30393	460	92053	5704497	3276	22772	4867990	840
2020	1	27500	1655	48291	720	75688	3039589		17845	3292110	
	2	29000	1250	455773		53676	7984983	800	10861	3.987.581	4481
	3	61000	6000	78656	415	84656	7083894	10550	33381	2990015	377
	4	4000	14718	77374	416	99175	11202160		51476	4022345	73590
	5	13000	1782	87441		51496	6284647	2772	3629	1229838	
	6	3000	30582	87713	65	109657	8059903	1000	24188	2919831	
	7	3000	4498	87855	240	89070	10100077	9164	22298	4043069	
	8	15000		88507		74042	4608909	24573	9128	1479255	30554
	9	18000	31421	80505		70842	8057796	5445	23413	5571619	266298
	10	26500		169723		69139	13334706	7509	43814	4916250	
	11	18000	2701	119329		86776	4661305	7059	5680	7778619	139500
	12	9500	4207	115147		76558	11300485	12188	23859	32553936	46584
Total		519300	188110	2590135	5730	1964284	181166073	137725	618244	116321231	745641

Table 2. Percentage of total sales by types

Product types	Sales	Cumulative Percentage
Flyer	519300	0.17%
Header	188110	0.06%
Pop	2590135	0.85%
Price card	5730	0.00%
Hanging	1964284	0.65%
Shelftalker	181166073	59.54%
Selftrip	137725	0.05%
Poster	618244	0.20%
Wobbler	116321231	38.23%
Brandliner	745641	0.25%
Total	304256473	100%

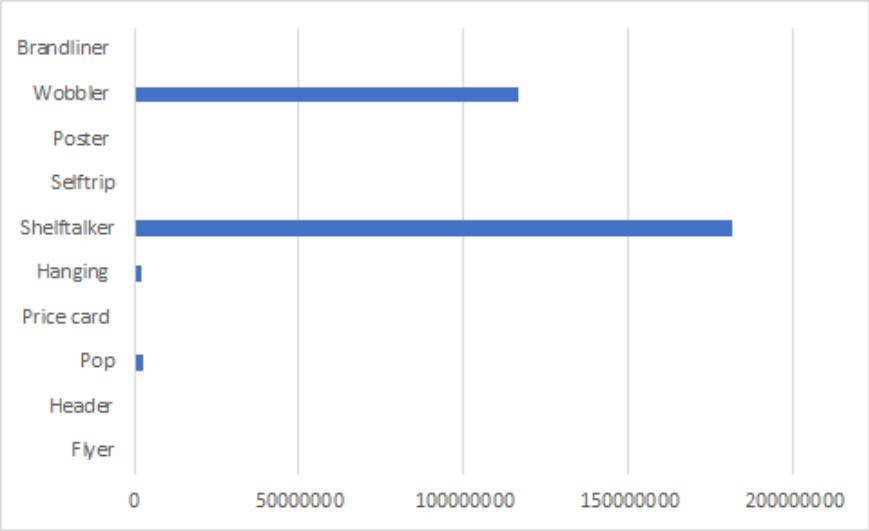

Figure 3. Number of product sales per type within 2 years in CV. Mitrakom Bintang Kemilau firm

We analyzed the proportion of the products produced by the firm. Data are summarized and grouped by the types of products. Table 2. show the proportion based on the types for each product. Products that are included in the cumulative percentage table are products which repeatedly produced almost most of the months for the past 2 years. Based on our finding, product type shelftalker is in high demand within year 2019 and 2020 followed by wobbler and have cumulative percentage of 59,54% and 38,23% with the following order. However, the other 8 types of products are not significant compared to shelftalker and wobbler with the differences of 99,43% in average of 8 products compared to the averages of shelftalker and wobbler combined. Figure 3 helps the visualization of how significant the products are according to each type. Hence, the scope of this study is to analyze method of time forecasting using moving average model in 2 types of products per se, wobbler and shelftalker, also analyze the whole production in this firm per month in two years.

5. Results and Discussion

From the data collection above, we can get the result by calculating using a simple moving average method. The task of our research is to use time series models for the year 2019 and 2020. Forecasting significant products by selecting the highest demand enables appropriate planning in the industry, specifically in this printing firm.

5.1 Graphical and Numerical Results

From the analysis, we visualize data series by plotting them and create 3 different types of line charts to describe the accuracy between the actual number of sales and the forecasts for 2 types of products, shelftalker and wobbler, and plotting one line graph to describe the relationship for all 10 types of products in the firm.

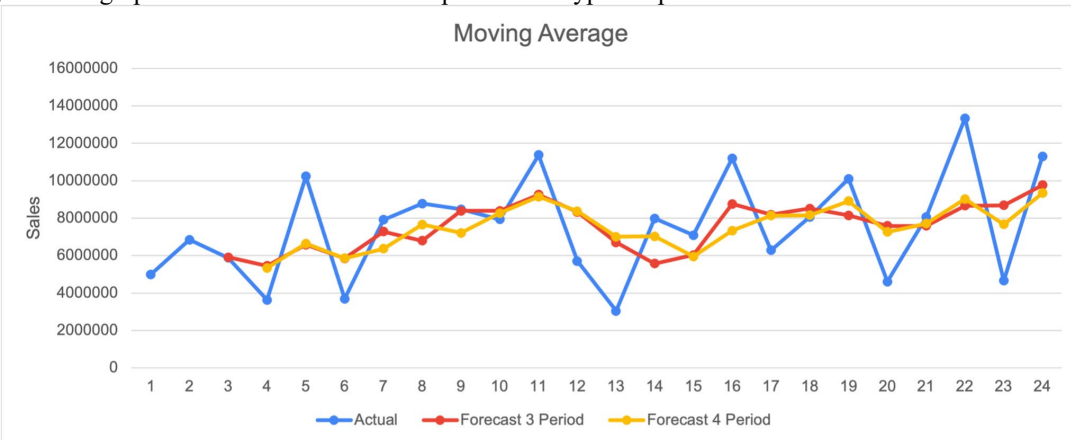

Figure 4. Single moving averages method for the number of shelftalker products in CV. Mitrakom Bintang Kemilau

Charts are usually easier to begin with for visualizing the movement and behavior of actual numbers. We begin to see that the line doesn't repeat itself periodically (Figure 4). There are depths and climaxes with the interval no more than 4 months sequentially. Beside this "up" and "down" movements, we can conclude that the overall direction of the number of shelftalker produced is increasing. The increasing trend from the line graph is the actual component of the primary data that we have. Beside the trend and seasonal component, there is an irregularity from the actual data as we can see from the graph above. We can conclude that the actual numbers have irregular aspects, also called "random aspect" which is the component that is always present in data, no matter whether they are time series or not.

Table 3. Averages of actual and forecasted data shelftalker using different series on single moving averages method

	Shelftalker 3 MA	Shelftalker 4 MA
MAPE	42.55	41.53
MAD	2,665,190.00	2,688,630.00
MSD	9,678,060,000,000.00	10,503,900,000,000.00

Table 3 shows the mean percentage absolute error (MAPE), mean absolute deviation (MAD), and mean square deviation (MSD) data of shelftalker moving averages method in 3 and 4 months. By establishing these two criteria of the period, we were able to determine the differences between the two methods. For series 3 month moving averages (MA), the error, MAPE, is 42.55 which means almost 3% slightly higher than 4 MA series. This is different from the number for MAD (deviation) and MSD (square deviation), the 3 months period is slightly less in comparison to the 4 months period moving average. There is an issue that has emerged from our findings, different expressions were found in these 3 types of accuracy of MAD along with MSD when comparing two different approaches to MAPE. Mean square deviation (MAD) and MSD showed that forecasted shelftalker using 3 moving averages is better as the number are lower than using 4 moving averages. On the contrary, if our perspective is based on the MAPE, it will express that the 4 MA is better than 3 MA and the 3 MA since the number is marginally lower than the other. In order to address this issue, based Both 3MA and 4MA techniques, we compared the percentage differences between both MAD along with MSD, and MAP. The result shows that there is 9.41% deviation of MAD and MSD combined. In this case, MSD contributed a great amount of the total deviation as outliers have a greater effect on MSD than on MAD. Meanwhile, as previously mentioned, the percentage differences on MAPE have a 3% margin of error. We can conclude that MAD and MSD combined have greater impact than MAPE itself, thus we can say from MAD and MSD results, 3 periods moving average is better compared to 4 periods.While deciding on which period is the best to choose for forecasting the products, it should be noted that they presented irregular pattern that increase the complexity of the prediction.

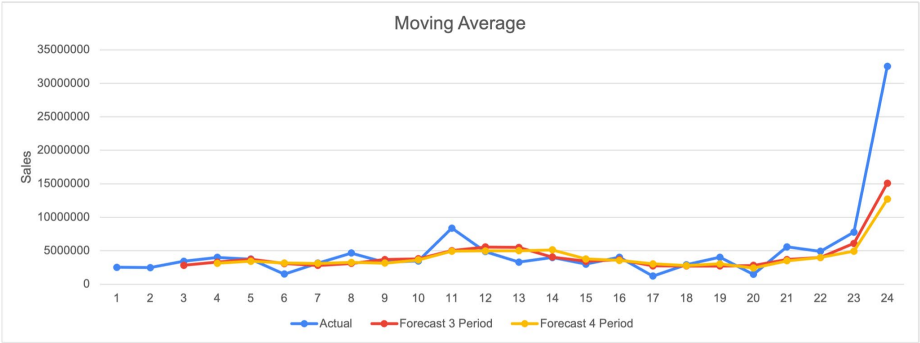

Figure 5. Single moving averages method for the number of wobbler products in CV. Mitrakom Bintang Kemilau

Table 4. Averages of actual and forecasted data wobbler using different series on single moving averages method

	Wobbler3 MA	Wobbler 4 MA
MAPE	46.66	47.44
MAD	2,653,330.00	2,779,750.00
MSD	36,811,900,000,000.00	41,797,900,000,000.00

Figure 5 shows the result of Single Moving Averages method which calculates the average of historical data in two different ways, 3 MA and 4 MA, with the same procedure and method applied Different from the first chart, the trend of this type of product indicates a relatively stable low demand and eventually fluctuates on the last two months in 2020. The relatively high fluctuations happening in the last two months of 2020 has the potential to influence the accuracy of the forecast. The averages error of forecasted demand are calculated and shown on the Table 4 above. Based on the number we have from the table, it seems that there is no significant difference between both of the techniques applied according to the standard error we used. Based on the numbers we have, the evidence shows that using three moving averages produces better results than using three moving averages.

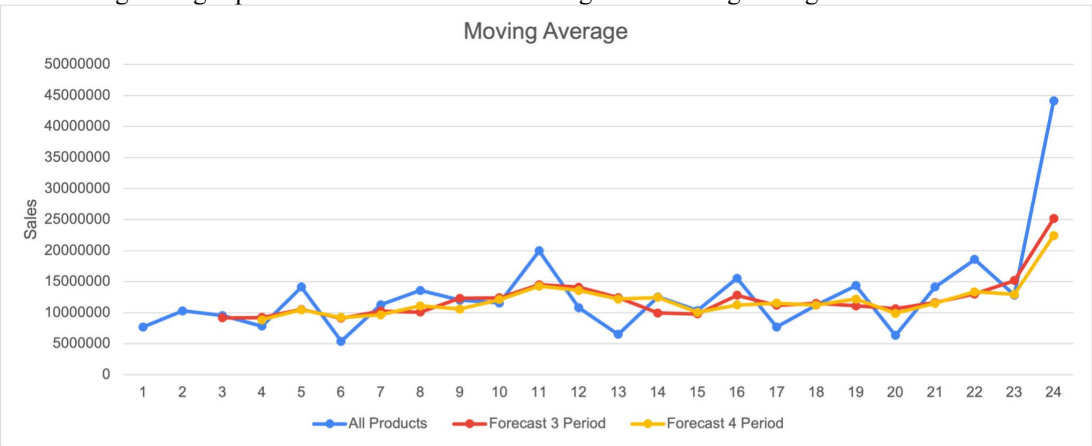

Figure 6. Single moving averages method for all products in CV. Mitrakom Bintang Kemilau

All types of products produced by CV. Mitrakom Bintang Kemilau that are mentioned in table 2 before are forecasted and plotted into a line graph. As the graph shows, the production in two years was in an irregular pattern. However, similar to other graphs in this paper, this data shows a positive trend line where there is a sharp rise in the last month of 2020. Single moving averages calculations are presented on table 5 where two different approaches are determined. From Table 5, it can be seen that the value of error for both approaches of the MA(Moving Average) are relatively small compared to the first and second products calculation that can be seen in Table 3 and Table 4. From these MAPE values we cannot conclude that the errors are as high as the last two products, either way we cannot say that the number itself represents a small error in forecasting all the products.

Table 5. Averages of actual and forecasted data for all main products using different series on single moving averages method

	All 3 MA	All 4 MA
MAPE	35.06	37.03
MAD	4,624,430.00	5,025,200.00
MSD	56748200000000.00	66571500000000.00

From the three graphs and tables shown above, our finding indicates that there are some irregularities in the productions that are eventually visualized from the differences between the actual productions and forecasting model using Single Moving Average Method on the interval 3 and 4 months. After plotting the averages and the errors, we can analyze that the smallest error using fMEPE is the data from all productions in the firm. Based on these findings, we can briefly analyze the trend, fluctuations,and irregularities by looking up at the graphic visualization and conclude that the smaller errors occur when the data have a fairly linear trend and definite rhythmic pattern of fluctuations. Thus, when we have smaller forecast errors, the better the model will work. In this case we are using a simple moving average model. Referring to the degree of accuracy we calculated before, with relatively high errors, we can conclude that both techniques present high error predictions in the 3 types of data along with the graphs we presented in this study.

5.2 Validation

For the validation, we use the Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE) methods to determine the error of the forecast. We get the average of each method as shown in Table 6.

	Shelftalker 3 MA	Shelftalker 4 MA	Wobbler 3 MA	Wobbler 4 MA	ALL 3 MA	ALL 4 MA
MAPE	42.55	41.53	46.66	47.44	35.06	37.03
MAD	2665190.00	2688630.00	2653330.00	2779750.00	4624430.00	5025200.00
MSD	9678060000000.00	10503900000000.00	36811900000000.00	41797900000000.00	56748200000000.00	66571500000000.00
Average Actual Data	7548586.38		5012867.17		12843502.25	

Table 6. Error summary of the forecasted data and the average of actual data

We chose to refer to the error value shown by MAPE, MAD, and MSD, since these accuracy measures being the most common measure of forecast error. Table 6 shows that among the other data being measured, the output of all goods has the smallest number of MAPE with the differences between two methods is 6% which indicates there are 6% differences if we went for one approach than the other for all types of product, whereas the differences of MAPE in shelftalker and wobbler between two different intervals are less than 6%. However, based on the number of MAPE, we can conclude that forecasting individual types of products (shelftalker and wobbler) are not better than forecasting the total products. As seen in Table 2, the probability of a high percentage of error MAPE from all forecasted goods can be influenced by missed revenue or zero demand within the ten products.

6. Conclusion

In this project, given that time series forecasting enables predicting the future through understanding the past, time series modeling and forecasting are important in a variety of practical domains. In the printing industry, forecasting future productions depend on capability to make predictions of significant products. After analyzing the graphic for both forecasted and actual data, error standards are calculated in measuring the differences between forecasted data in two different techniques and actual data are conducted. From the previous graphical and numerical results, we have concluded that the 3 different types of data itself are not in a regular state with some numbers of fluctuations occurring within the 2 years period of 2019 and 2020.

Analysis of the data for the number of products differ in 3 ways has resulted in strong irregular components. This can happen as a result of the standard policy which the firm used in producing and selling the products to the customers.

The firm is using the MTO (Make To Order) method and as a result, production demand does not always follow a predictable pattern.When data has a reasonably linear trend and a definite rhythmic pattern of variations, a moving average model works well. However, perhaps due to the MTO method used by the company, our data does not reveal any linear or rhythmic patterns as moving average models simply smooths out the variations in the results.

The accuracy of various statistical techniques as well as the MAPE predictor were investigated in this paper. For that purpose, 2 years of sales data were collected. Based on the number of MAPE, MAD, and MSD estimated with the number of MAPE more than 30% but less than 50% for two of the three types of data provided in this paper, we cannot say that the number of errors represents a high inaccuracy model. We can compare the calculated MAPE or forecast accuracy among companies or industries while we look at the nature of the demand they are trying to forecast. We can conclude that the forecasting method using a single moving average model for our data that has most irregular patterns resulted in 30%-50% errors. As a result, if the errors we have are relatively high based on all of the firm considerations, the paper suggests that there is no point in proceeding with a strategy focused on weak forecast data without any changes both to the forecasting system we used and the production approaches used in this firm. However, there are some methods used in forecasting data for more desirable forecasting results also with different results in the degree of errors.

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