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Proposed Improvement of Forecasting Using Time Series Forecasting of Fast Moving Consumer Goods

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ABSTRACT

The company discussed in this paper is a national distributor firm that distributes FMCG products. The PPIC division in the company is responsible for forecasting the demand using the combination of the moving average method and intuition according to the interest of the company. However, the PPIC staff never measures the accuracy of their forecasting method. This research paper aims to evaluate the forecasting methods used to predict the demands of 12 classes of A SKU. Four-time series forecasting methods are particularly implemented, i.e., ARIMA, moving average (MA), double exponential smoothing (DES), and linear regression (RL). Forecasting using the ARIMA method is carried out by considering the stationarity of the average and variance of the historical data points. Forecasting using DES is carried out by using the optimal alpha and gamma values of the ARIMA method. The results show that the performance of each forecasting method varies, depending on which demands of class A SKU are predicted. Based on these results, the current forecasting method utilized by the company should be improved using the time series forecasting methods leading to the smallest error values for each class of A SKU.

Keyword*:FMCG, Moving average, Minitab, ARIMA, Double exponential smoothing, Linear regression*

1. INTRODUCTION

Fast-moving consumer goods (FMCG) are a part of the non-oil and gas industry. FMCG consists of daily needs with fast movements, such as food, clothing, and household needs. Although FMCG consumption has decreased due to changes in people's consumption priorities, FMCG is an essential need of every household thus its consumption will never stop.

Apart from being affected by priority changes in people's consumption, FMCG consumption is also affected by the flow of the supply chain. When each stage of the supply chain runs smoother, the consumer interest in buying these goods will also increase (Manders, Caniëls, & Th, 2016). In this case, distribution activities are crucial to ensure a smooth supply chain. The distributor is a company that provides distribution services to manufacturing or retail companies. There is a difference in the distributor's role and it depends on the supply chain structure of each country (Chopra & Meindl, 2016). The retail conditions in developed countries tend to be consolidated as a whole with the purchase of FMCG products in large quantities, while retail in developing countries has limitations in the storage systems so that FMCG products are purchased in small volumes (Chopra and Meindl, 2016). This can be reflected in the high contribution of transportation and savings to GDP in 2019, which is around 5.6% (Hirschmann, 2020). Before COVID-19 pandemic, the development of domestic business is currently in a state of rapid growth (Tannady, Nurprihatin and Hartono, 2018)

The company discussed in this paper is a national distribution company engaged in the distribution of FMCG products from the P&G manufacturing company. The company encountered various challenges, such as a large amount of Stock Keeping Units (± 1,900 ID SKUs), fluctuations in SKU changes (upsize or downsize), managerial related issues, and limited company budgets. The Production Planning and Inventory Control (PPIC) division is a division at the company that has a responsibility in regulating the number of SKUs

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that must be ordered and stored according to the predicted number of demand. For predicting the number of SKU demand, PPIC division employees currently use the combination between the Moving Average method and intuition based on current managerial interests. Furthermore, the accuracy of the implemented forecasting method is not measured. Consequently, it leads to potential lost sales and inventory issues at the beginning of each month. Therefore, any unnecessary inventory should be minimized if cannot be eliminated (Tannady *et al.*, 2019). The accumulation of the inventory can lead to a decrease in the quality (Christian *et al.*, 2021). A previous study discussed the transportation of the inventory under the developed vehicle routing modeling (Nurprihatin and Lestari, 2020). Another research pointed out the distribution routes that are directly related to transportation costs (F. Nurprihatin *et al.*, 2019) and solved using the heuristics method (Filscha Nurprihatin *et al.*, 2019).

Based on the classification results carried out by the PPIC division, there are 12 SKUs included in class A items out of a total of 437 SKUs that are still active from January 2018 to the end of July 2020. Figure 1 presents one of the error measurements, i.e., the calculation of the mean absolute percentage error (MAPE), for 12 active SKUs of class A based on the current forecasting method and actual demand data from companies. It can be seen that the current forecasting method produces an average error of 90.24%. Therefore, an improvement in the forecasting method is crucial so that the demand prediction can be more accurate and closer to the actual conditions.

This study hence aims to evaluate several existing forecasting methods and perform a comparison between these forecasting methods with the ones currently used by the company. The comparison is conducted by comparing two types the forecasting accuracy measurements, i.e., *Mean Absolute Deviation* (MAD) and *Mean Absolute Percentage Error* (MAPE), obtained from four-time series forecasting methods, i.e., autoregressive integrated moving average (ARIMA), moving average (MA), double exponential smoothing (DES), and linear regression (RL). The results lead to an appropriate forecasting method for each SKU.

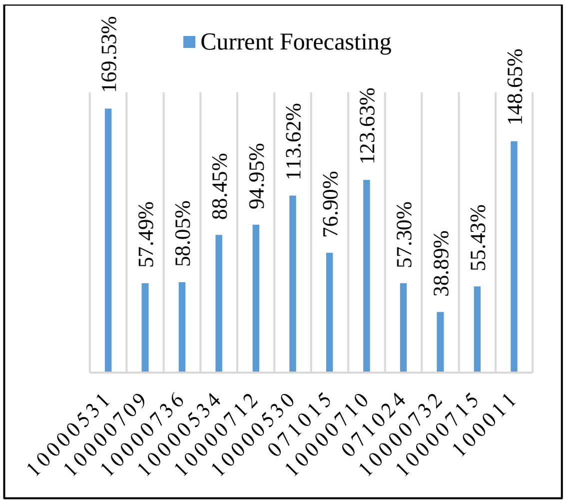

Figure 1. Error Measurement
(Source: Reseacher, 2020)

2. METHODOLOGY

2.1 Research Objects

This research analyses the object in the form of all classes of A SKU in the company. The collected datasets are the SKU classification data carried out by the company and the weekly demands from January 2018 to July 2020.

2.2 Research Flow Chart

The steps of this research start with collecting data. The collected data consists of SKU classification data from companies, weekly demands from January 2018 to July 2020, the forecasting demands of the company's PPIC division, and interviews with experts to determine the condition of the company. Afterward, four forecasting methods, i.e., ARIMA, MA, DES, and RL, are implemented using MiniTab 18 software. The results of the optimal ARIMA model will be used to determine the alpha value (level) and gamma values (trend) for the forecasting using the DES method. Furthermore, the MAD, MAPE, and MSE values are calculated as measurement indicators for each forecasting method, including the forecasting methods currently used by the company. These measurement indicators serve as a basis to determine the most appropriate forecasting method to predict the demand of each SKU.

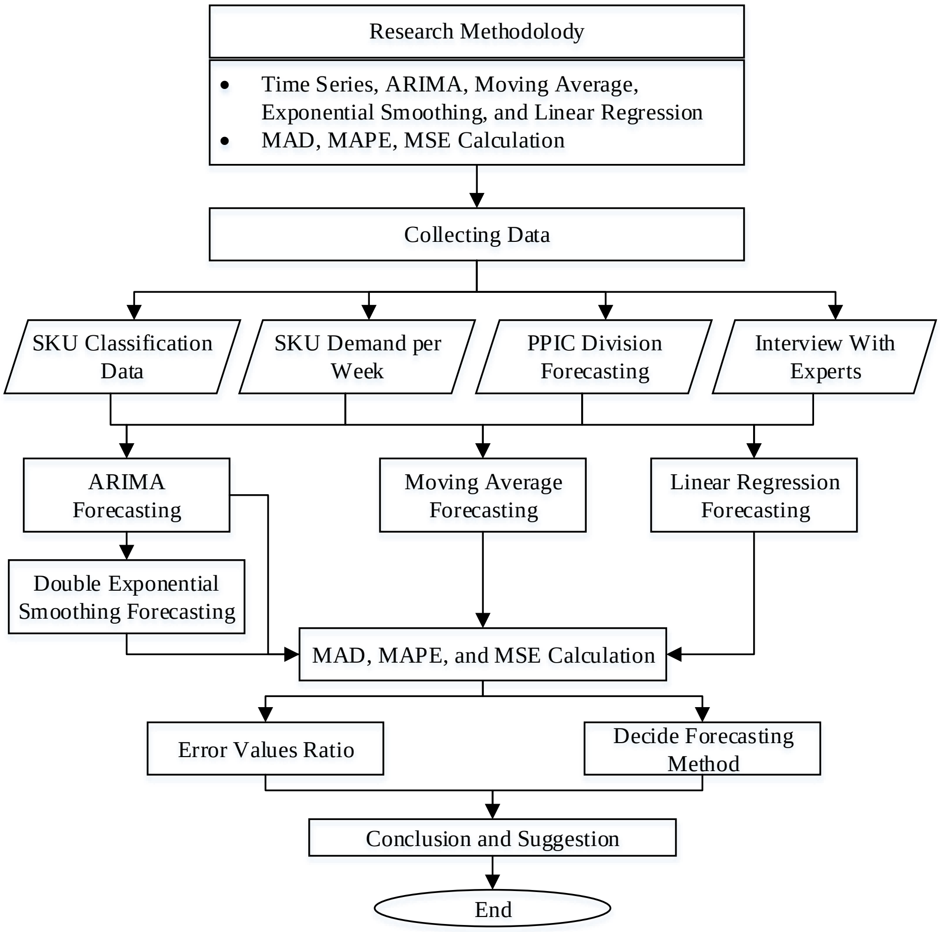

Figure 2. Flow Chart Research

(Source: Researcher, 2020)

The object of this research is class A SKU at the company. The selection of class A SKU as the object of research is because class A SKU is the SKU with the highest percentage of overall demand so that it contributes 80% of the company's revenue. The data collection phase is done by collecting primary data through direct observation in the field. In addition, primary data was obtained by conducting direct interviews with the patient manager of the company. Figure 2 shows a sequence of the research flow chart in conducting this research.

3. RESULTS AND DISCUSSION

ARIMA, moving average, double exponential smoothing, and linear regression forecasting are carried out for class A SKUs that are active from January 2018 to June 2020 based on the classification results that have been carried out by the PPIC division. There are 12 SKUs that will be forecasted, namely codes 10000531, 10000709, 10000736, 10000534, 10000712, 10000530, 071015, 10000710, 071024, 10000732, 10000715, 100011.

3.1 ARIMA Forecasting

Forecasting using the ARIMA method is carried out using Minitab 18 software. The stages of ARIMA forecasting using MiniTab 18 are described as follows:

1. Perform the average stationary test on the data by observing the distribution of trends in the data. There are 12 class A SKUs that will be tested for stationary trends.
2. Perform the variance stationary test on the data with a box-cox plot. Data with a stationary variance will have a rounded value = 1. If the variance of the data is not stationary, data transformation must be performed.
3. Observe the distribution of trends from the transformed data. If the average of the data transformation is still not stationary then we need to differencing the data.

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4. Perform autocorrelation function (ACF) and partial autocorrelation function (PACF) testing phases after conducting the differencing data. If five lines in the data distribution cross the limit of the initial lag, the data cannot be used.
5. If the data can be used, then trial and error are carried out for determining the ARIMA model. Selection of the optimal ARIMA model is based on several criteria: (1) the p-value model which must be ≤ 0.05 so that the model can be said to be significant, (2) the p-value on the L-Jung Box must be ≥ 0.05 so that the residue on the model can be said to be of insignificant value, and (3) the model has the smallest mean square error (MSE).

Table 1 explains the ARIMA model that was selected after processing the data according to the steps above.

3.2 Moving Average Forecasting (MA)

Forecasting using the MA method takes the average length of the data for the past 3 periods (Maricar, 2019). Figures 3 to 14 illustrate the plot between the actual demand and the fitted demand produced by the MA forecasting method.

Table 1. ARIMA Model

SKU	ARIMA Model (p,d,q)	MS	Details
10000531	4,1,2	2,487,108,080	Can be used
10000709	3,0,4	4,649,265,827	Can be used
10000736	2,1,3	2,343,548,943	Can be used
10000534	2,1,3	1,174,064,338	Can be used
10000712	2,1,3	1,469,822,041	Can be used
10000530	2,1,3	695,614,178	Can be used
71015	3,0,3	320,301,684	Can be used
10000710	5,1,2	241,715,389	Can be used
71024	2,0,1	202,293,232	Can be used
10000732	1,1,2	348,122,109	Can be used
10000715	2,1,0	29,433,241	Can be used
100011	4,1,3	6,854,426	Can be used

(Sources: Primary Data Processing, 2020)

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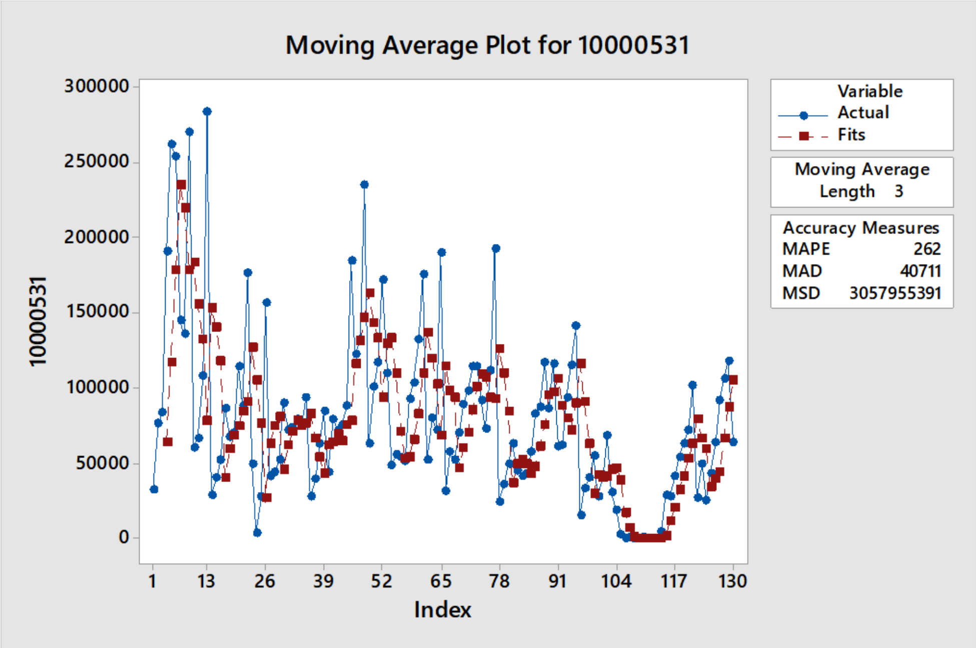

Figure 3. Moving Average SKU 10000531
(Source: Primary Data Processing, 2020)

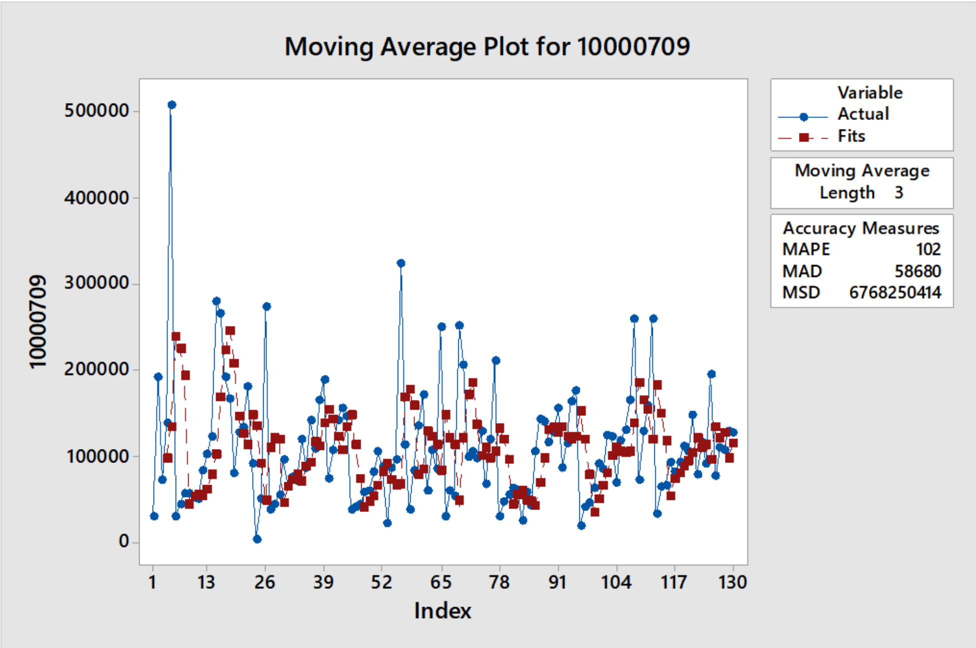

Figure 4. Moving Average SKU 10000709
(Source: Primary Data Processing, 2020)

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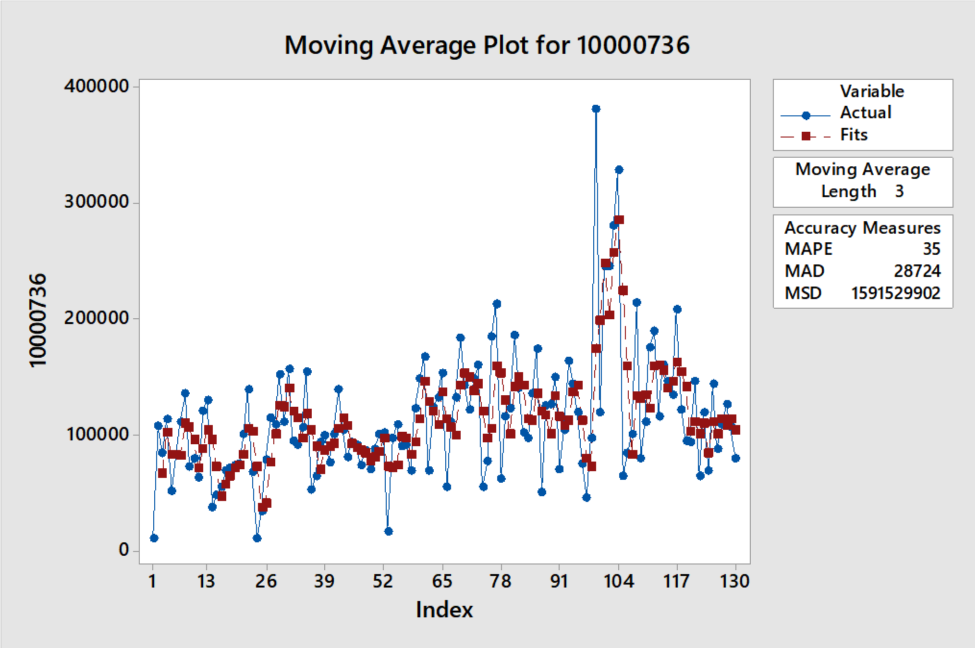

Figure 5. Moving Average SKU 10000736
(Source: Primary Data Processing, 2020)

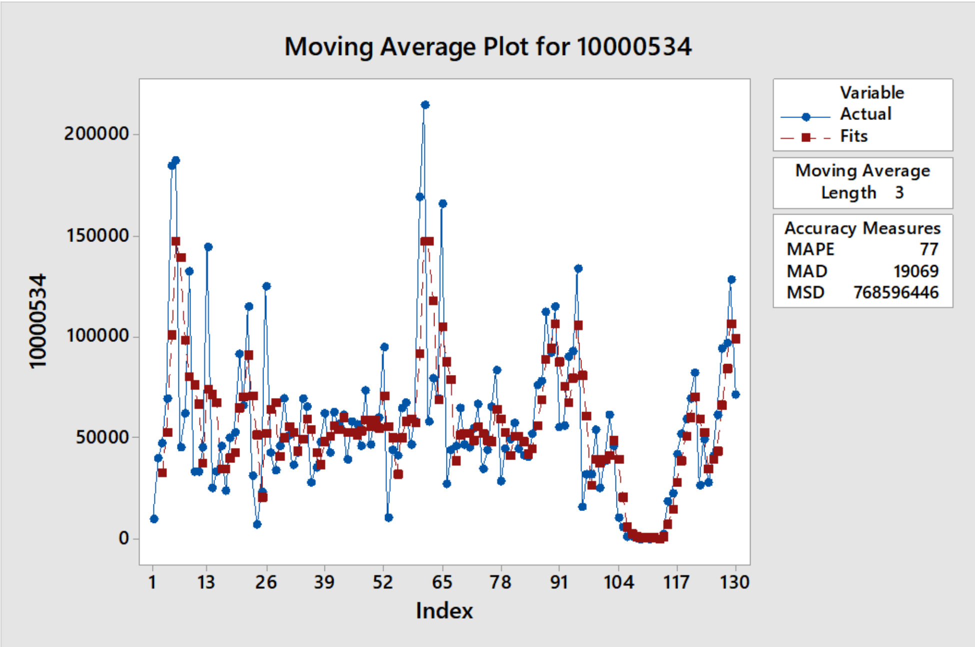

Figure 6. Moving Average SKU 10000534
(Source: Primary Data Processing, 2020)

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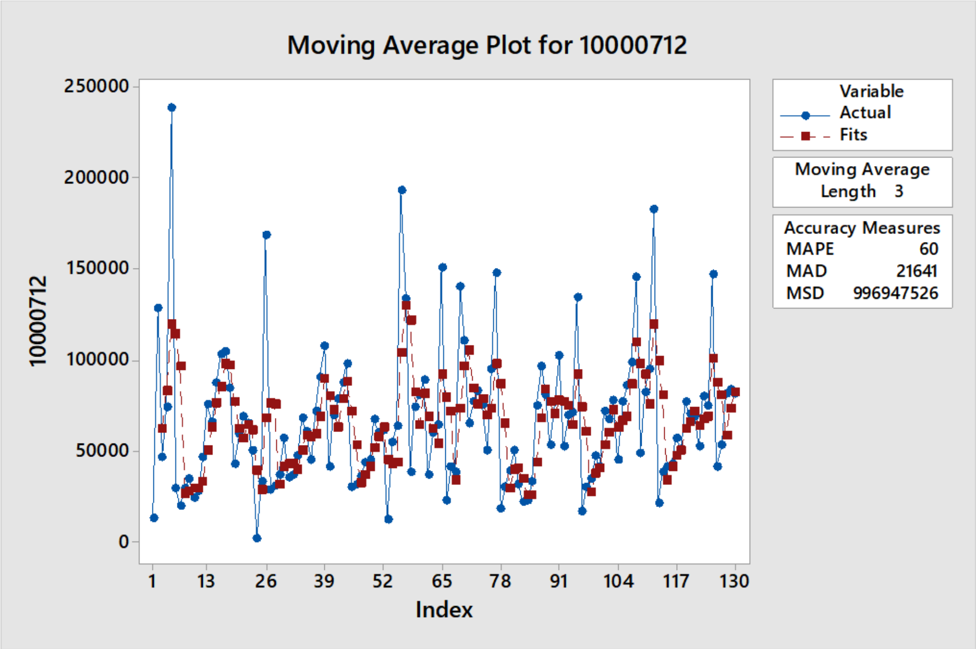

Figure 7. Moving Average SKU 10000712
(Source: Primary Data Processing, 2020)

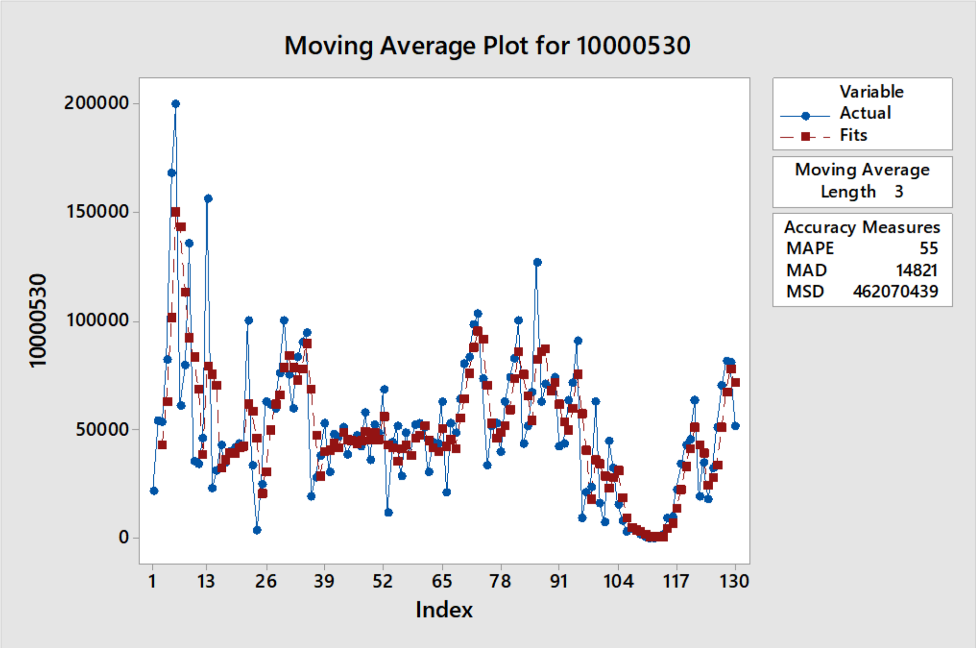

Figure 8. Moving Average SKU 10000530
(Source: Primary Data Processing, 2020)

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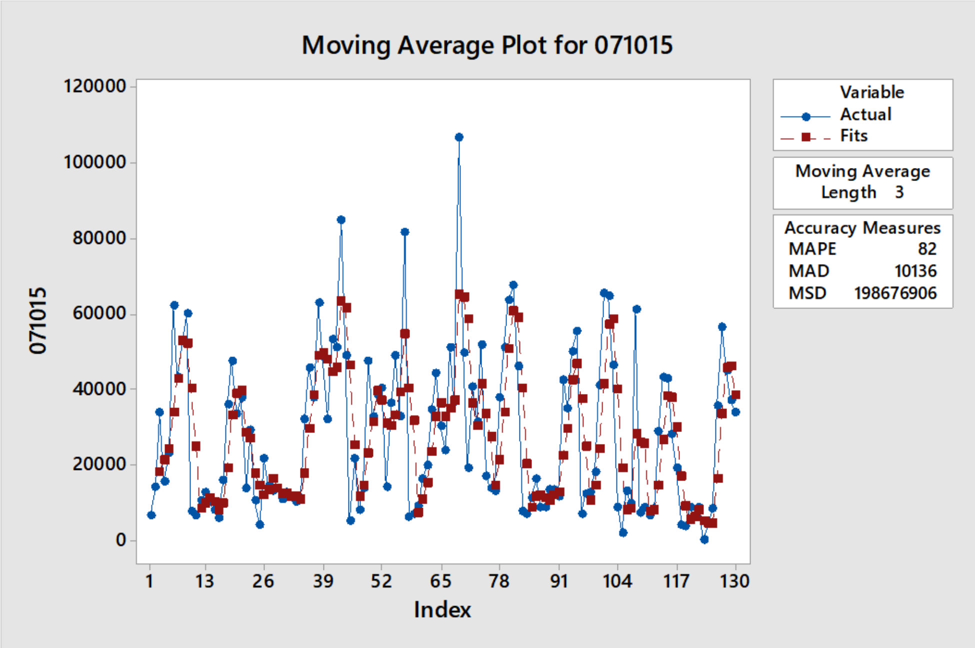

Figure 9. Moving Average SKU 071015
(Source: Primary Data Processing, 2020)

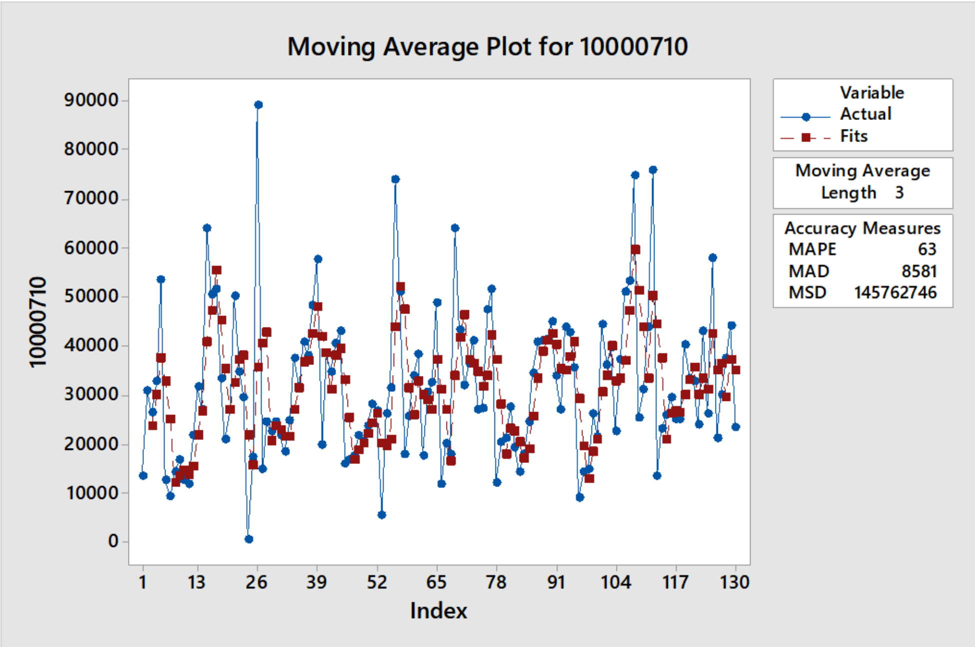

Figure 10. Moving Average SKU 10000710
(Source: Primary Data Processing, 2020)

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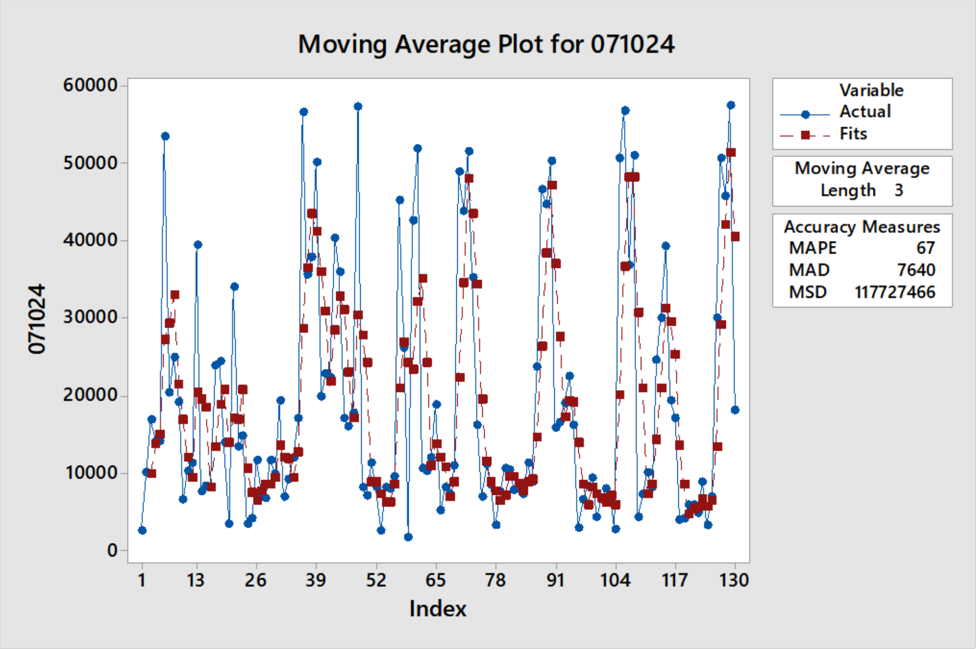

Figure 11. Moving Average SKU 071024
(Source: Primary Data Processing, 2020)

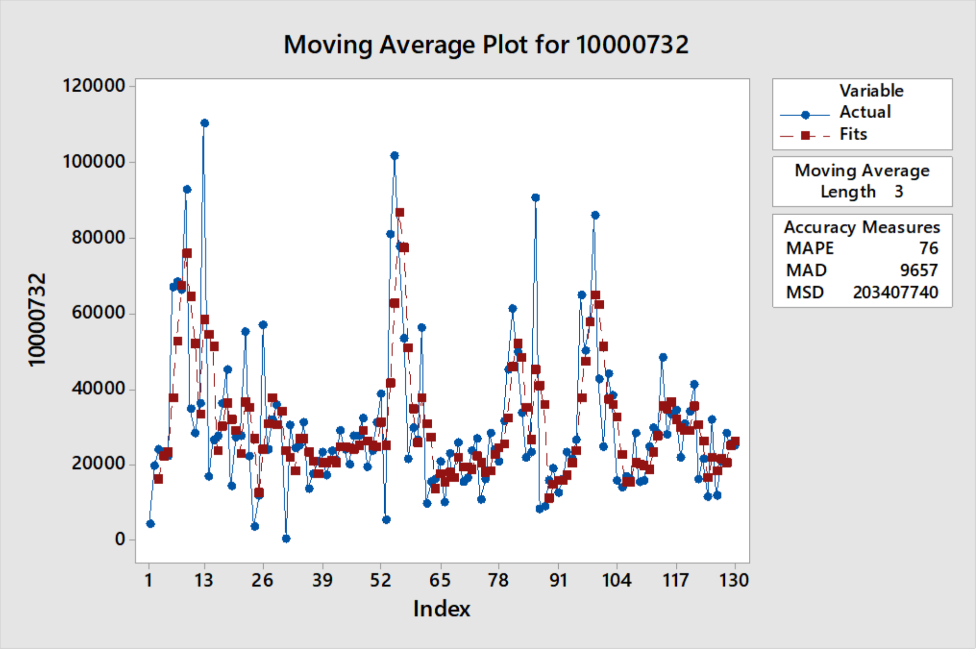

Figure 12. Moving Average SKU 10000732
(Source: Primary Data Processing, 2020)

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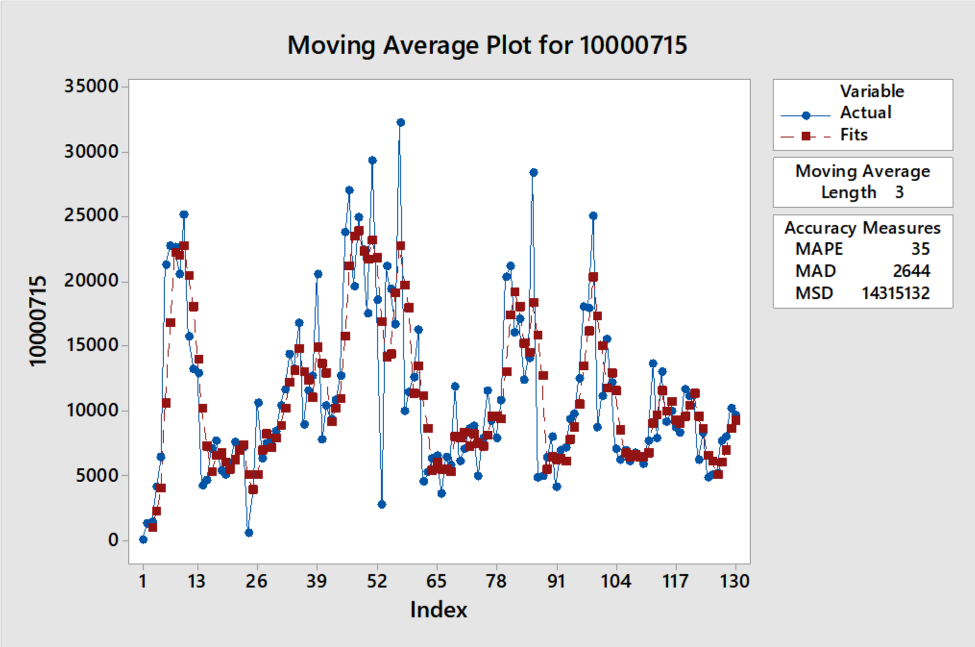

Figure 13. Moving Average SKU 10000715
(Source: Primary Data Processing, 2020)

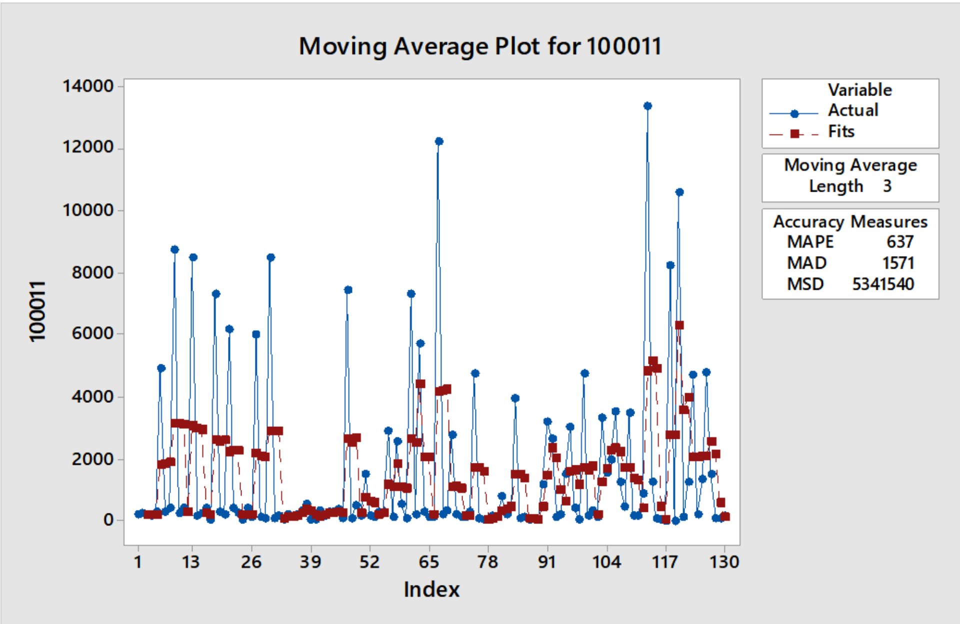

Figure 14. Moving Average SKU 100011
(Source: Primary Data Processing, 2020)

The accuracy values of the MA method are represented by MAPE, MAD, and MSE. The smaller MAPE, MAD, and MSE values indicate that the forecasting method being carried out is more accurate.

3.3 Double Exponential Smoothing Forecasting (DES)

The alpha (level) and the gamma (trend) values from DES forecasting are determined based on the equivalence with the optimal ARIMA model. Table 2 shows the alpha and gamma values for each SKU.

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Table 2. Alpha and Gamma Values for every SKU

SKU	Alpha	Gamma
10000531	1.0237	0.01207
10000709	0.991529	0.002686
10000736	1.01084	0.0122
10000534	1.05909	0.00152
10000712	0.980938	0.016811
10000530	1.08004	0.01235
071015	1.0529	0.01512
10000710	1.0078	0.01523
071024	1.08557	0.01166
10000732	1.04981	0.01322
10000715	0.727	0.002478
100011	1.11076	0.00248

(Source: Primary Data Processing, 2020)

3.4 Linear Regression Forecasting (RL)

The Simple Linear regression method is utilized for Linear Regression Forecasting. The independent and dependent variables are the period and number of demand from consumers, respectively. Table 3 describes the forecasting equations obtained by the linear regression method.

Table 3. Linear Regression for Every SKU

SKU	Equation
10000531	$Y_t = 118561 - 611 \times t$
10000709	$Y_t = 115054 - 75 \times t$
10000736	$Y_t = 78073 + 540 \times t$
10000534	$Y_t = 68142 - 175.4 \times t$
10000712	$Y_t = 61415 - 81.2 \times t$
10000530	$Y_t = 69624 - 288.7 \times t$
071015	$Y_t = 29125 - 17.3 \times t$
10000710	$Y_t = 28217 + 52.6 \times t$
071024	$Y_t = 28217 + 23.6 \times t$
10000732	$Y_t = 34566 - 61.6 \times t$
10000715	$Y_t = 12132 - 16.2 \times t$
100011	$Y_t = 1206 + 5.03 \times t$

(Source: Primary Data Processing, 2020)

Table 4. Forecasting Results for SKU 10000531

SKU 10000531						
Week	ARIMA	MA	DES	RL	Current Condition	Actual Demand
1	80,061	95,993	63820.75	38542.922	9,600	64,295
2	87,804	95,993	64646.34	37932.1	73,260	52,023
3	100,015	95,993	65471.93	37321.278	34,020	53,266
4	72,712	95,993	66297.52	36710.456	105,000	99,087
5	84,711	95,993	67123.12	36099.635	24,000	68,817

(Source: Primary Data Processing, 2020)

Table 5. Forecasting Results for SKU 10000709

SKU 10000709						
Week	ARIMA	MA	DES	RL	Current Condition	Actual Demand
1	99,005	121,625	126720.6	105,187.95	57,876	127,944
2	102,239	121,625	125494.7	105,112.64	96,600	90,080
3	118,535	121,625	124268.9	105,037.33	73,500	99,812
4	116,218	121,625	123043	104,962.02	197,316	180,616
5	100,290	121,625	121817.2	104,886.71	63,000	135,670

(Source: Primary Data Processing, 2020)

Table 6. Forecasting Results for SKU 10000736

SKU 10000736						
Week	ARIMA	MA	DES	RL	Current Condition	Actual Demand
1	81,208	103,988	79,670	148,876	31,560	79,199
2	101,224	103,988	80,443	149,416	75,360	80,313
3	131,934	103,988	81,216	149,957	59,280	78,099
4	85,282	103,988	81,989	150,497	117,000	91,346

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SKU 10000736						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
5	118,815	103,988	82,762	151,038	348,000	72,912

(Source: Primary Data Processing, 2020)

Table 7. Forecasting Results for SKU 10000534

SKU 10000534						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	76,743	98,934	69,725	45,161	26,340	71,568
2	60,196	98,934	71,451	44,986	31,680	33,710
3	82,326	98,934	73,177	44,810	35,430	39,774
4	80,691	98,934	74,902	44,635	37,500	40,884
5	64,675	98,934	76,628	44,460	11,250	38,569

(Source: Primary Data Processing, 2020)

Table 8. Forecasting Results for SKU 10000712

SKU 10000712						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	69,645	82,536	82,787	72,048	36,876	81,941
2	68,834	82,536	83,577	72,130	62,076	61,399
3	68,057	82,536	84,366	72,211	60,900	58,738
4	68,837	82,536	85,156	72,292	125,916	92,494
5	68,658	82,536	85,946	72,373	21,000	88,485

(Source: Primary Data Processing, 2020)

Table 9. Forecasting Results for SKU 10000530

SKU 10000530						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	49,554	71,403	49,865	31,809	23,430	51,614
2	44,349	71,403	50,545	31,520	52,260	38,714
3	66,899	71,403	51,225	31,232	36,000	36,758
4	54,297	71,403	51,905	30,943	58,500	50,362
5	46,809	71,403	52,585	30,654	9,461	47,860

(Source: Primary Data Processing, 2020)

Table 10. Forecasting Results for SKU 071015

SKU 071015						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	24,676	38,770	33,761	26,855	22,698	33,957
2	22,458	38,770	33,725	26,837	5,760	12,992
3	21,160	38,770	33,690	26,820	8,640	11,726
4	20,874	38,770	33,655	26,803	22,464	15,082
5	22,391	38,770	33,619	26,785	3,911	9,417

(Source: Primary Data Processing, 2020)

Table 11. Forecasting Results for SKU 10000710

SKU 10000710						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	31,278	35,023	23,238	35,114	28,056	23,329

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SKU 10000710						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
2	25,516	35,023	23,314	35,166	5,376	30,840
3	40,426	35,023	23,391	35,219	39,564	30,481
4	28,748	35,023	23,467	35,272	28,560	45,071
5	30,989	35,023	23,543	35,324	81,861	43,487

(Source: Primary Data Processing, 2020)

Table 12. Forecasting Results for SKU 071024

SKU 071024						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	18,457	40,463	14,553	20,534	26,274	18,211
2	18,554	40,463	14,362	20,557	28,224	9,952
3	18,588	40,463	14,170	20,581	5,184	7,666
4	18,589	40,463	13,978	20,604	4,032	9,332
5	18,579	40,463	13,786	20,628	9,216	8,132

(Source: Primary Data Processing, 2020)

Table 13. Forecasting Results for SKU 10000732

SKU 10000732						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	29,847	26,251	25,271	26,497	10,752	24,987
2	31,366	26,251	25,585	26,436	26,880	24,633
3	32,066	26,251	25,899	26,374	18,942	19,824
4	32,389	26,251	26,214	26,313	23,940	31,218
5	32,538	26,251	26,528	26,251	27,300	32,389

(Source: Primary Data Processing, 2020)

Table 14. Forecasting Results for SKU 10000715

SKU 10000715						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	9,320	9,297	9,746	10,015	25,473	9,647
2	9,613	9,297	9,957	9,999	26,880	17,514
3	9,571	9,297	10,169	9,983	28,900	11,902
4	9,512	9,297	10,380	9,967	12,390	19,939
5	9,549	9,297	10,591	9,951	35,784	14,162

(Source: Primary Data Processing, 2020)

Table 15. Forecasting Results for SKU 100011

SKU 100011						
Week	**ARIMA**	**MA**	**DES**	**RL**	**Current Condition**	**Actual Demand**
1	3,702	120	134	1,864	678	4,716
2	306	120	93	1,869	696	198
3	326	120	53	1,874	1,536	1,365
4	2,270	120	12	1,879	4,476	4,788
5	1,618	120	28	1,884	960	1,517

(Source: Primary Data Processing, 2020)

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Table 16. Mean Absolute Deviation (MAD)

SKU	ARIMA	MA	DES	RL	Current Condition
10000531	28,113	29,733	11,957	30,176	29,182
10000709	31,920	26,543	26,504	29,890	38,454
10000736	67,383	71,184	60,645	98,333	74,431
10000534	28,025	54,033	29,013	10,472	16,461
10000712	14,507	12,287	11,706	14,082	29,762
10000530	8,564	26,341	6,863	13,830	17,805
071015	9,389	22,135	17,134	13,026	11,993
10000710	10,408	7,786	11,251	7,762	18,832
071024	7,895	29,804	4,974	9,922	7,040
10000732	5,031	4,083	3,635	4,181	5,946
10000715	5,120	5,336	4,504	4,797	14,272
100011	956	2,397	2,453	1,662	1,115

(Source: Primary Data Processing, 2020)

3.5 Forecasting Results

Five-week demand forecasting is performed by each forecasting model produced by the aforementioned methods. Tables 4 to 15 present the predicted demands resulted from each aforementioned forecasting method, the current forecasting method employed by the company, and actual demands. Also, each table is dedicated for each class of A SKU. These tables are produced to measure the forecasting accuracy of the proposed forecasting methods which will be further described in the next section.

3.6 Forecasting Error Calculation

This section describes forecast error calculation that shows the accuracy of the forecasting methods. Moreover, a comparison among forecasting methods is shown in this section to show the effectiveness of the proposed forecasting methods. Two types of error measurement are utilized, i.e., MAD and MAPE (Kurniagara, 2017; Anggraeni, 2019; Irawan and Laksito, 2019; Maricar, 2019; Nurprihatin, Jayadi and Tannady, 2020). Tables 16 to 17 consecutively present the results of MAD and MAPE values for each forecasting method implemented to predict the future demands of each SKU. In addition, Figures 15 and 16 show the comparison charts for MAD and MAPE values for each forecasting method, respectively.

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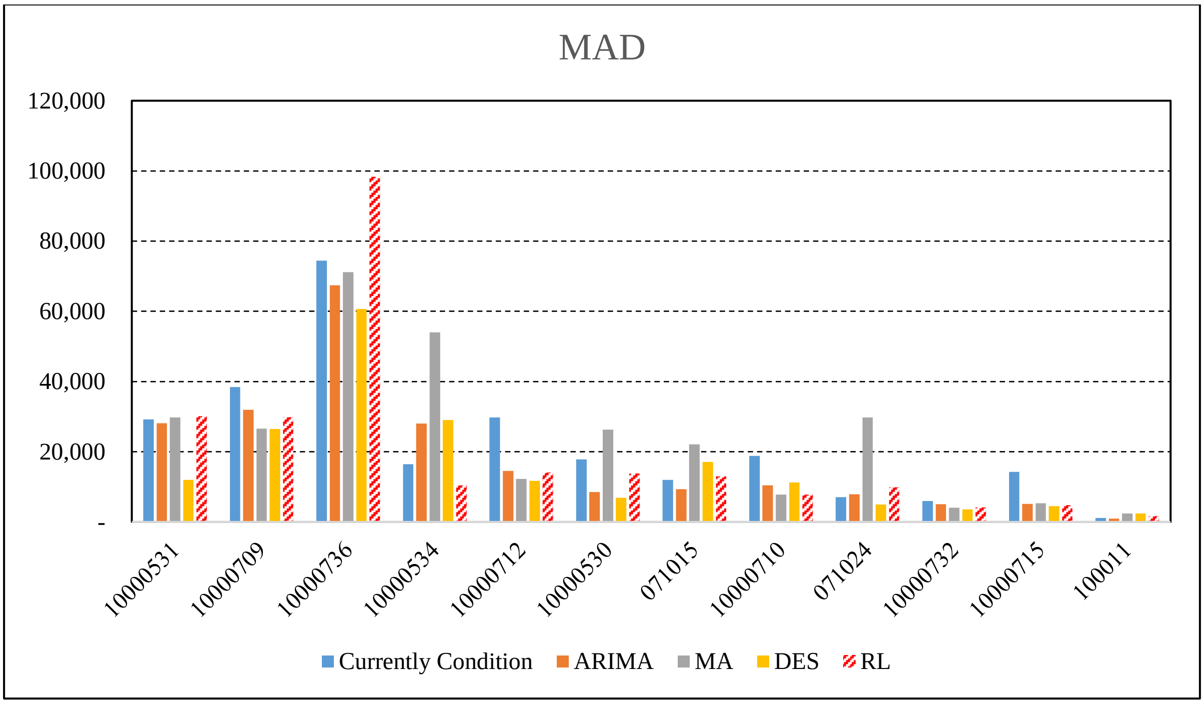

Figure 15. MAD Graph
(Source: Researcher, 2020)

Table 17. Mean Absolute Percentage Error (MAPE) Calculation

SKU	ARIMA	MA	DES	RL	Current Condition
10000531	32.4%	31.0%	18.2%	81.4%	169.5%
10000709	29.5%	21.8%	21.4%	28.5%	57.5%
10000736	57.0%	68.5%	73.3%	65.4%	58.0%
10000534	38.4%	54.6%	39.2%	23.3%	88.4%
10000712	21.1%	14.9%	13.9%	19.5%	94.9%
10000530	14.3%	36.9%	13.4%	44.3%	113.6%
071015	42.0%	57.1%	50.9%	48.6%	102.9%
10000710	33.6%	22.2%	48.0%	22.0%	123.6%
071024	42.5%	73.7%	35.2%	48.2%	57.3%
10000732	16.0%	15.6%	13.9%	15.9%	38.9%
10000715	53.6%	57.4%	44.0%	48.1%	55.4%
100011	99.7%	2003%	10013%	88.8%	148.7%

(Source: Primary Data Processing, 2020)

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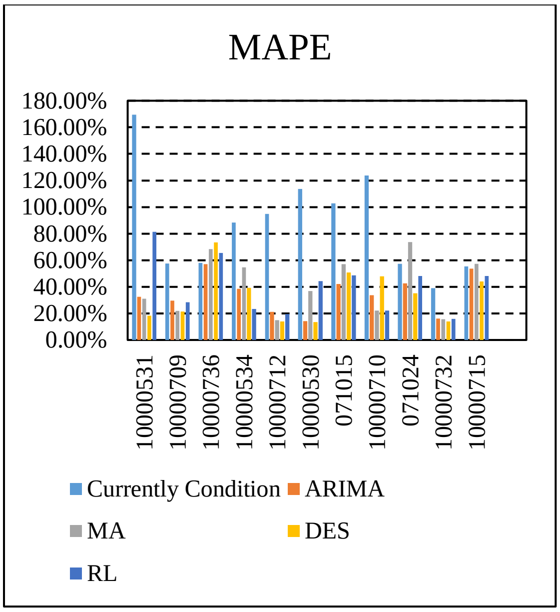

Figure 16. MAPE Graph
(Source: Primary Data Processing, 2020)

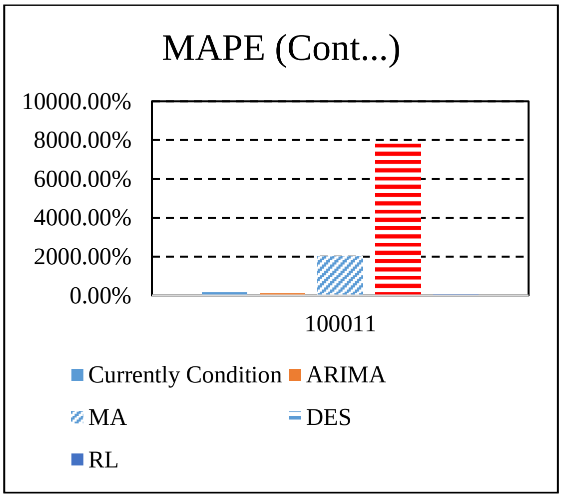

Figure 17. MAPE Graph (Cont)
(Source: Primary Data Processing, 2020)

Table 18. Forecasting For Every SKU

SKU	Proposed Forecasting Method	Model
10000531	DES	1.0237 , 0.01207
10000709	ARIMA	3,0,4
10000736	DES	1.01084 , 0.01220
10000534	Linear Regression	$Y_t = 68142 - 175.4 \times t$
10000712	DES	0.980938 , 0.016811
10000530	DES	1.08004 , 0.01235
71015	ARIMA	3,0,3
10000710	Linear Regression	$Y_t = 28217 + 52.6 \times t$
71024	DES	1.08557 , 0.01166
10000732	DES	1.04981 , 0.01322
10000715	DES	0.727 , 0.0024778
100011	ARIMA	4,1,3

(Source: Primary Data Processing, 2020)

Then determine the appropriate forecasting method for each SKU. Table 18 describes the appropriate forecasting methods to be used for each SKU.

4. CONCLUSION

Based on the research results, it can be concluded that the forecasting method used by the company today produces a higher error value than the time series forecasting method. Therefore, the company needs to make improvements for predicting the demands of each SKU.

The results show that each SKU requires a different forecasting method, depending on the historical data characteristics of each SKU. Thus, the implementation of various forecasting methods is intended to obtain forecasting results with higher accuracy. The most appropriate forecasting methods used for forecasting each SKU are listed as follows: (1) double exponential smoothing for SKU 10000531, SKU 10000736, SKU 10000712, SKU 071024, SKU 10000732, SKU 10000715 (2) ARIMA for SKU 10000709, SKU 10000530, SKU 071015, SKU 100011 (3) linear regression for SKU 10000534, SKU 10000710. Based on these results, double exponential smoothing is the most suitable forecasting method among all the employed forecasting methods.

The suggestions related to future research are to perform classification on SKU classes to ensure the SKU availability and inventory in the warehouse management system, to control orders and store goods by considering demand uncertainty and waiting time, and to calculate cycle service levels (CSL) by controlling distribution logistics. Further study can also discuss 8 pillars of TPM and 5S to increase the effectiveness (Nurprihatin, Angely and Tannady, 2019).

REFERENCES

Anggraeni, D. T. (2019) "Forecasting Harga Saham Menggunakan Metode Simple Moving Average dan Web Scrapping," *Jurnal Ilmiah Matrik*, 21(3), pp. 234–241.

Chopra, S. and Meindl, P. (2016) *Supply Chain Management: Strategy, Planning, and Operation*. 6th ed. New York: Pearson Education.

Christian, M. *et al.* (2021) "Business Performance Determinants of Salted Fish Distribution in Kapuk During the COVID-19," *Journal of Distribution Science*, 19(6), pp. 29–39. doi: 10.15722/jds.19.6.202106.29.

Hirschmann, R. (2020) *Contribution to GDP by Industry Indonesia 2019*, *Statista*.

Irawan, R. Y. and Laksito, W. (2019) "Penerapan Metode Double Exponential Smoothing Untuk Peramalan Tingkat Indeks Pembangunan Manusia," *Jurnal TIKomSiN*, 7(2), pp. 18–28.

Kurniagara (2017) "Penerapan Metode Exponential Smoothing Dalam Memprediksi Jumlah Siswa Baru (Studi Kasus: SMK Pemuda Lubuk Pakam)," *Jurnal Pelita Informatika*, 6, pp. 19–25.

Maricar, M. A. (2019) "Analisa Perbandingan Nilai Akurasi Moving Average dan Exponential Smoothing untuk Sistem Peramalan Pendapatan pada Perusahaan XYZ," *Jurnal Sistem dan Informatika*, 13(2), pp. 36–45.

Nurprihatin, F. *et al.* (2019) "A Distribution Strategy Using A Two-step Optimization to Maximize Blood Services Considering Stochastic Travel Times," in *IOP Conference Series: Materials Science and Engineering*. doi: 10.1088/1757-899X/650/1/012043.

Nurprihatin, Filscha *et al.* (2019) "The Extension Analysis of Natural Gas Network Location-Routing Design Through the Feasibility Study," *Journal of Applied Research on Industrial Engineering*, 6(2), pp. 108–124. doi: 10.22105/jarie.2019.174164.1082.

Nurprihatin, F., Angely, M. and Tannady, H. (2019) "Total Productive Maintenance Policy to Increase Effectiveness and Maintenance Performance Using Overall Equipment Effectiveness," *Journal of Applied Research on Industrial Engineering*, 6(3), pp. 184–199. doi: 10.22105/jarie.2019.199037.1104.

Nurprihatin, F., Jayadi, E. L. and Tannady, H. (2020) "Comparing Heuristic Methods' Performance for Pure Flow Shop Scheduling Under Certain and Uncertain Demand," *Management and Production Engineering Review*, 11(2), pp. 50–61. doi: 10.24425/mper.2020.133728.

Nurprihatin, F. and Lestari, A. (2020) "Waste Collection Vehicle Routing Problem Model with Multiple Trips, Time Windows, Split Delivery, Heterogeneous Fleet and Intermediate Facility," *Engineering Journal*, 24(5). doi: 10.4186/ej.2020.24.5.55.

Tannady, H. *et al.* (2019) "Process Improvement to Reduce Waste in the Biggest Instant Noodle Manufacturing Company," *Journal of Applied Engineering Science*, 17(2), pp. 203–212. doi: 10.5937/jaes17-18951.

Tannady, H., Nurprihatin, F. and Hartono, H. (2018) "Service Quality Analysis of Two of the Largest Retail Chains with Minimart Concept in Indonesia," *Business: Theory and Practice*, 19, pp. 177–185. doi: 10.3846/BTP.2018.18.