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Forecasting Roof Tiles Production with Comparison of SMA and DMA Methods Based on n-th Ordo 2 and 4

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ABSTRACT

This research aims to predict roof tile production trends at one of the roof tile companies in Kebumen to assist company management in determining and providing management recommendations for the tile production that occurs. A comparison of Single Moving Average (SMA) and Double Moving Average (DMA) Forecasting methods was used to better accommodate trends in roof tile production data optimally. Where the forecast is presented for several steps ahead, and is equipped with a value measuring the accuracy of the forecast using Mean Absolute Percentage Error (MAPE), on roof tile production transaction data over 60 months, namely January-December 2019 to January-December 2023 to produce a monthly forecast for predicting roof tile production with n-th ordo 2 and 4. The total sample of training data processed was 1,415,987 records which were roof tile production transaction data, as well as data in January 2024 as test data (to test the accuracy of the forecast). The results of testing the forecast results produced a MAPE calculation of 6.6% for SMA with n-th ordo 2, while for n-th ordo 4 it was 7.2%. The MAPE value for DMA is 6.3% for n-th ordo 2, while for n-th ordo 4 it is 8.2%, which means the accuracy level is very good, namely above 90%. Based on the MAPE results obtained, the DMA method with n-th ordo 2 is a suitable method for carrying out periodic forecasting for roof tile companies in carrying out the production process to maintain stability and avoid unexpected events.

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A. INTRODUCTION

Roof tiles are one of the main supporting products in making buildings that have value to meet the needs of people's building or house roofs, a commodity whose demand will continue to increase along with the increasing density of Indonesia's population (Tundo & Mahardika, 2023). Roof tile production business players must focus more on improving internal governance, starting from production management to menu recommendations that are in demand by customers, so that they can survive and continue to develop (Riki, 2020). For this reason, roof tile production business owners must be able to take into account the series of production business flows first, as well as implement production management that helps evaluate price decisions, customer demand, and the quality of the roof tiles (Tobing, 2022). Apart from that, roof tile production business owners need to implement appropriate production management, to avoid losses caused by excessive demand or unavailability of stock (Febrian et al., 2020).

Based on observations from several roof tile production companies in Kebumen City, predictive calculations and scientific data analysis have not been carried out in determining roof tile production. Generally, roof tile manufacturing company owners only prepare raw materials in large quantities at once without paying attention to incoming demand or available inventory (Tundo & Sela, 2018). This occurs due to a lack of control over the production process. The worst consequence that can arise from this problem is a decrease in customer trust and loyalty which can result in large losses and loss of potential customers, as well as reduced claims for returning roof tiles or losses can also occur due to non-fulfillment of refund claims (Tripathi et al., 2019). Another solution is to use forecasting methods or what is usually called forecasting to predict the amount of production that may need to be prepared at some point in the future (Bhuyan et al., 2023).

Forecasting allows companies to determine future conditions based on past and current conditions, thus enabling companies, especially roof tile production operations managers, to understand what events may occur and what actions are appropriate to understand. The forecasting function serves as the basis for capacity planning, budgeting, sales planning, production and inventory planning, resource planning, and raw material purchasing planning (Weerathunga et al., 2020). Forecast results enable stakeholders to easily make decisions regarding inventory availability and budgeted cost stability. It can be concluded that for roof tile production company managers, especially in production management, forecasting is a very important need in determining the business strategy of roof tile company owners. The prediction function is one of the five important roles of data mining (Sutopo et al., 2023). Data mining is the extraction of hidden information in large databases, facilitating the discovery of important information hidden behind databases containing very large amounts of data (Rahat et al., 2019).

One of the forecasting methods that is widely used is the Single Moving Average (SMA) and Double Moving Average (DMA) methods. Several previous studies have applied similar methods in this research, including: Siswanto et al. (2021), using this method for forecasting inventory, resulting in an inventory forecasting system that makes it easier to determine the amount of inventory in subsequent years Astuti et al. (2019) applied the SMA method to predict sales of children's toys for the next period in toy stores and created a computerized system so that sales of toy products were more effective and efficient; and (Maknunah, 2019) applying the DMA method in forecasting applications in determining the acceptance of new cooperative members, to see the trend (increase/decrease) in interest in applicants so that the selection of new cooperative member acceptance can be correct. In essence, moving average forecasting is widely used to determine the trend of a series of periods (Febrian et al., 2020). From several previous studies, it is known that all existing research only determines the overall forecast for the next period, in contrast to this research, this research not only knows the total number of forecasts but also compares SMA and DMA with n-th ordo 2 and 4 as efforts to find the best alternative for carrying out the forecasting process.

This research discusses the application of SMA and DMA comparison methods to predict roof tile production trends, forecasting production trends which are carried out for monthly periods with n-th ordo 2 and 4. The data processed is production transaction data over 60 months, namely January-December. 2019 to January-December 2023. The monthly forecast is aimed at predicting roof tile production trends based on comparing results from SMA and DMA.

Apart from that, this research also discusses how the SMA and DMA methods perform in forecasting, as measured by the Mean Absolute Percentage Error (MAPE).

B. METHODS

1. Object of Research

The object of scrutiny is roof tile production at TH Abadi Kebumen. The data used is production transaction data for 60 months, namely transactions from January to December 2019-2023. The total transaction data processed as training data is 1,415,987 records, which is the entire transaction data. Meanwhile, the test data uses transaction data for January 2024.

2. Data processing and Analysis techniques

Data processing and analysis technology applies data mining technology (Saifullah et al., 2023). As previously mentioned, data mining is the process of extracting data to find interesting patterns from large amounts of data and storing them in databases, data warehouses, or other information storage places (Tundo & Uyun, 2020). A data warehouse is an object-oriented, integrated, time-varying data store that stores data in a non-volatile format to support management decision-making (Singh, 2019). The following steps were taken to explore the possibility that the information in the tile production database could be used as useful knowledge for tile production managers:

a. Data collection

   Data collection was carried out by observing existing documents from roof tile companies, especially TH Abadi Kebumen which was used as a sample. The data collected is roof tile production transaction data that occurred over 60 months from January to December 2019 to January to December 2023. Next, the data acquisition stage is carried out, namely the data acquisition stage or the data placement stage. During the update phase, the stored data is updated and adjusted to current events. The stored data is accessed during the acquisition phase and summarized again for further processing.

b. Data pre-Processing

   The preprocessing phase converts the raw data into a format suitable for analysis (Ogundare & Wiggins, 2018). This process aims to clean data by separating unnecessary data or correcting data that is not appropriate.

c. Algorithm Implementation

   At this stage, the data that has been collected will be processed using the SMA and DMA comparison method to obtain a forecast for monthly period roof tile production with n-th ordo 2 and 4. This will make it easier to manage roof tile production and make decisions related to production by business management roof tile.

d. Evaluation

   This phase creates the results of the data mining process which provides information patterns. This phase is explained in detail in the “Results and Discussion” section.

3. Data selection

Data selection from a set of operational data must be done before the information mining phase begins in Knowledge Discovery in Databases (Rahmalia, 2021). The data obtained regarding roof tile production is raw data in Excel format based on transactions obtained in response to roof tile orders by customers. Where the data was obtained directly from the TH Abadi Kebumen Company by conducting observations and interviews with company leaders. The data selection process is the selection of parameters that influence tile production, such as raw materials (land, molding equipment, grain, water), costs, customer demand, tile inventory, etc. Then, important parameters are selected to estimate roof tile production. Based on mutual agreement with the agency, decisions are taken based on existing land, customer demand, and roof tile supplies as parameters.

4. Data Pre-Processing

At this stage, the data cleaning process is carried out, namely ensuring that the data to be processed is data that is not duplicated, inconsistent, and not defective, and is correlated with the processing that will be carried out. Because this research is forecasting using the SMA and DMA methods, the data selection process was carried out again, focusing on forecasting roof tile production.

5. Single Moving Average (SMA) Method

SMA is a forecasting method that focuses on taking a group of observation values and looking for the average value to predict the future period (Wang et al., 2020). A similar thing was stated by Dewi & Chamid (2019), that the SMA method is a technique for calculating the average of a number from the latest actual value, which is then updated as new available values and used to make forecasts in subsequent periods. More specifically Alex et al. (2023) stated that the SMA method has two special properties, namely that to make forecasting, historical data is needed over a certain period, the longer the moving averages, the smoother the moving averages will be. The stages of implementing the SMA method in this research are outlined in Table 1.

Table 1. Stages of implementation of SMA nth ordo 2 and 4

Stages	Process
Recapitulation of roof tile production data	The initial process before calculating the SMA is to recap the total roof tile production from January to December 2019 to 2023 which will be calculated by forecasting based on 2 periods and 4 periods.
Recording daily transaction data for roof tile production	After all roof tile production is collected and then totaled in one month to be recorded, then the data is used as training data which is useful for testing the forecasting that will be made.
Make roof tile production forecasts with SMA	At this stage, calculate the roof tile production forecast using the SMA equation which produces two forecasts, namely monthly forecasts using n-th ordo (n=2) and (n=4) with the accuracy level test data used as Mean Absolute Percentage Error (MAPE), If the results are <10% then this SMA can be used to forecast the next data. If the results are > 10% then the data needs to be trained again to reach the minimum error limit.

Mathematically, the SMA method is as written in the following equation:

$$S' = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-n+1}}{n} \quad (1)$$

Description: S' is the first moving average value in period t; x_t is the value of the second moving average in period t; and n is the number of limits in the moving average (n-th ordo).

6. Double Moving Average (DMA) Method

DMA is a double moving average where one group average is calculated and then the second group calculates the moving average that was produced by the first group (Khairina, Khairunnisa, Hatta, & Maharani, 2021). In essence, DMA is a continuation of SMA, where to calculate DMA you need to look for forecasting results from SMA first. A similar thing was stated by (Mustapa, Latief, & Rohandi, 2019), that the DMA method is a double-moving average calculation technique that forwards the results of the SMA method for re-forecasting with the aim that the forecasting results will be more optimal. The stages of DMA implementation are the same as in Table 3 above, only the calculation method used changes. Mathematically, the DMA method is as written in the following equation (Mustapa et al., 2019), (Hudiyanti, Bachtiar, & Setiawan, 2019):

a. Determine the first smoothing value (S'_t)

$$S' = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-n+1}}{n} \quad (2)$$

b. Determine the second, third, ...n-th values for smoothing as (S''_t)

$$S'' = \frac{S'_t + S'_{t-1} + S'_{t-2} + \cdots + S'_{t-n+1}}{n} \quad (3)$$

c. Determine the constant value results (a)

$$a_t = 2S'_t - S''_t \quad (4)$$

d. Determine the resulting slope value as the steepness point (b_t)

$$b_t = \frac{2}{n-1}(S'_t - S''_t) \quad (5)$$

Description: S' is the first moving average value in period t; S'' is the value of the second moving average in period t; x_t is the value of the second moving average in period t; and n is the number of limits in the moving average (n-th ordo). Determining future periods will happen when the at and bt values are considered for alpha calculations. The moving normal is n arranged, and s is the length of the regular cycle. This thinks about assessed distinctive k values to decide their effect on determining exactness. Values of s speaking every day or week by week regularly were chosen to play down the cruel squared blunder on the preparing set. Determine the results of the forecasting value (F_{t+m}) as follows:

$$F_{t+m} = a_t + b_t m \tag{6}$$

Description: F_{t+m} is forecasting results in the next period; X_t is the actual data value in period t; m is the number of subsequent periods to be predicted; a_t is the number of period constant values t; and b_t is the trend value results in the appropriate data.

7. Mean Absolute Percentage Error (MAPE)

Estimating execution is calculated by calculating the esteem of the contrast in real requests assessed over a particular period. MAPE could be a degree of relative blunder that gives mistake extent comes about, which demonstrates whether the mistake extent is moo or tall (Syahdan, Arif, & Megawati, 2022), (Selvachandran et al., 2019). The equation for MAPE is as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|PE_t| \tag{7}$$

with:

$$PE_t = \left(\frac{X_t - F_t}{X_t}\right)100\% \tag{8}$$

Description: n is the number of testing data periods; PE_t is the percentage error; X_t is actual value in period t; and F_t is forecast value in period t. The MAPE score categories for the procedure are shown in Table 2. This technique works well when the MAPE value is below 10%. This method performs better when the resulting MAPE value is lower (Khan & Ahmad, 2019).

Table 2. MAPE value level categories

MAPE value	Categories
< 10%	Very Good
10% - 20%	Good
20% - 50%	Enough
> 50%	Poor

C. RESULT AND DISCUSSION

Detailed data pre-processing can be seen in Table 3 and Table 4 (Tundo, 2022).

Table 3. Roof tile production data influenced by the parameters Ln, Dm, Sp

Month	Year	Land (Ln)	Demand (Dm)	Supplies (Sp)	Production
January	2019	50000	34000	875	20613
February	2019	55000	31600	500	23800
March	2019	53000	29950	400	25016
April	2019	40000	28720	450	24206
May	2019	45000	29860	230	25516
June	2019	42000	29050	300	25107
July	2019	32000	25050	250	27031
August	2019	56000	32550	200	30072

Month	Year	Land (Ln)	Demand (Dm)	Supplies (Sp)	Production
September	2019	45000	30050	250	27558
October	2019	42000	29550	300	25134
November	2019	40000	27700	500	23731
December	2019	30000	24100	100	26010
January	2020	25000	21050	150	23841
February	2020	20000	18690	340	24317
March	2020	25000	21740	100	23045
April	2020	15400	14230	590	12780
May	2020	15500	14760	330	23544
.....	.....	.....	.....	.....	.....
.....	.....	.....	.....	.....	.....
December	2023	48000	27460	210	27500

Table 4. Roof tile production data is used to carry out the forecasting process.

Month	Year	Production
January	2019	20613
February	2019	23800
March	2019	25016
April	2019	24206
May	2019	25516
June	2019	25107
July	2019	27031
August	2019	30072
September	2019	27558
October	2019	25134
November	2019	23731
December	2019	26010
January	2020	23841
February	2020	24317
March	2020	23045
April	2020	12780
Mey	2020	23544
.....	.....	.....
.....	.....	.....
December	2023	27500

1. Forecasting SMA

The forecast results for roof tile production for January 2024 using Forecasting SMA n-th ordo 2 are presented in Table 5, using equation (1), the results were found to be 26744 tile production based on SMA n-th ordo 2.

Table 5. SMA n-th ordo 2

Month	Year	Production	S'
January	2019	20613	-
February	2019	23800	-
March	2019	25016	23143
April	2019	24206	24340.66667
May	2019	25516	24912.66667
June	2019	25107	24943
July	2019	27031	25884.66667

Month	Year	Production	S'
August	2019	30072	27403.33333
September	2019	27558	28220.33333
October	2019	25134	27588
.....	.....	.....	.....
.....	.....	.....	.....
December	2023	27500	26744
January	2024	Forecasting = 26744	

Meanwhile, the forecast results for roof tile production for January 2024 using Forecasting SMA n-th ordo 4 are presented in Table 6, with a result of 27346.4 roof tile production based on SMA n-th ordo 4.

Table 6. SMA n-th ordo 4

Month	Year	Production	S'
January	2019	20613	-
February	2019	23800	-
March	2019	25016	-
April	2019	24206	-
May	2019	25516	23830.2
June	2019	25107	24729
July	2019	27031	25375.2
August	2019	30072	26386.4
September	2019	27558	27056.8
October	2019	25134	26980.4
.....	.....	.....	.....
.....	.....	.....	.....
December	2023	27500	27346.4
January	2024	Forecasting = 27346.4	

Based on the forecast results of roof tile production in January 2024 using Forecasting SMA n-th ordo 2 and 4, if implemented in a trend graph, it is clear that SMA n-th ordo 2 is more inclined to actual roof tile production. This is proven by the MAPE value of 6.6%, compared to n-th ordo 4 of 7.2%. The graphic trend is visible in Figure 1.

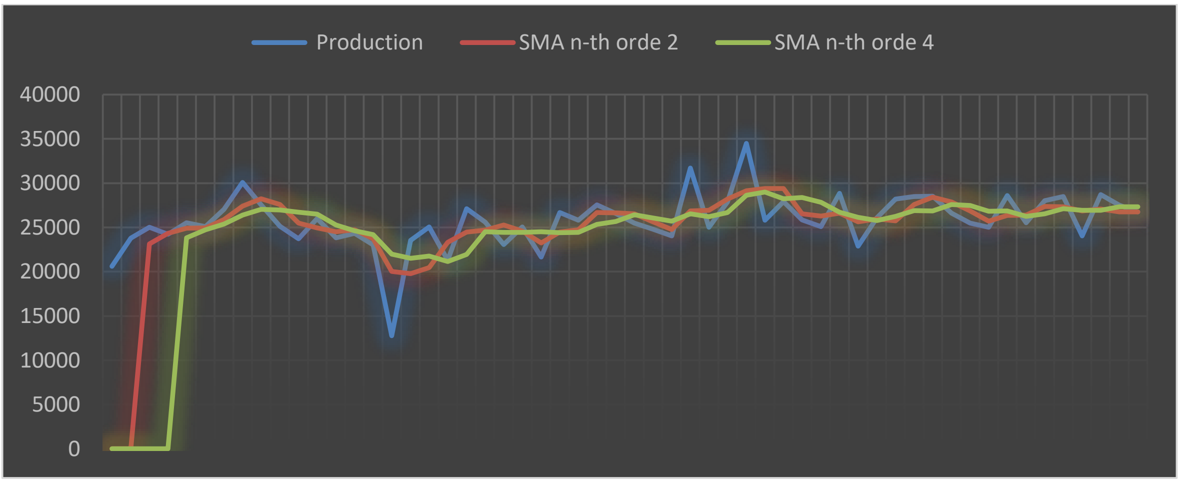

Figure 1. Trend forecasting based SMA n-th ordo 2 and 4 on Roof tile Production

2. Forecasting DMA

The results of the forecast for roof tile production for January 2024 using Forecasting DMA n-th ordo 2 found a result of 26455.1 roof tile production based on equations (1), (2), (3), (4), and (5). In equation 1, look for the SMA value (S') which is continued to equation (2) by looking for the S'' value, which means doing a moving average 2x times that of (S'), then look for at using equation (3) in the form of the constant value obtained, After that, look for the resulting slope value (bt) as a steepness point using equation (4), then find the DMA forecasting results based on equation (5), which are shown in Table 7.

Table 7. DMA n-th orde 2

Production	S'	S''	a_t	b_t	F_{t+m}
20613	-	-	-	-	-
23800	-	-	-	-	-
25016	23143	-	-	-	-
24206	24340.66667	-	-	-	-
25516	24912.66667	24132.11111	25693.222	780.5556	26473.77778
25107	24943	24732.11111	25153.889	210.8889	25364.77778
27031	25884.66667	25246.77778	26522.556	637.8889	27160.44444
30072	27403.33333	26077	28729.667	1326.333	30056
27558	28220.33333	27169.44444	29271.222	1050.889	30322.11111
25134	27588	27737.22222	27438.778	-149.222	27289.55556
.....	.....	.....	.....	.....	.....
27500	26744	26888.44444	26599.556	-144.444	26455.11111
Forecasting = 26455.11111					

The process carried out is the same as in Table 8, but here we use the n-th orde 4, which means doing a moving average 4x times that of (S'). The results of DMA forcasting based on n-th orde 4 are 28089.12 roof tile production, in detail shown in Table 8.

Table 8. DMA n-th orde 4

Production	S'	S''	a_t	b_t	F_{t+m}
20613	-	-	-	-	-
23800	-	-	-	-	-
25016	-	-	-	-	-
24206	-	-	-	-	-
25516	23830.2	-	-	-	-
25107	24729	-	-	-	-
27031	25375.2	-	-	-	-
30072	26386.4	-	-	-	-
27558	27056.8	25475.52	28638.08	1581.28	30219.36
25134	26980.4	26105.56	27855.24	874.84	28730.08
.....	.....	.....	.....	.....	.....
27500	27346.4	26975.04	27717.76	371.36	28089.12
Forecasting = 28089.12					

The results of the roof tile production forecast for January 2024 using Forecasting DMA n-th ordo 2 and 4, if implemented in a trend graph, it is clear that the DMA n-th ordo 2 is more inclined to actual roof tile production. This is proven by the MAPE value of 6.3%, compared to n-th ordo 4 of 8.2%. The graphic trend is visible in Figure 2.

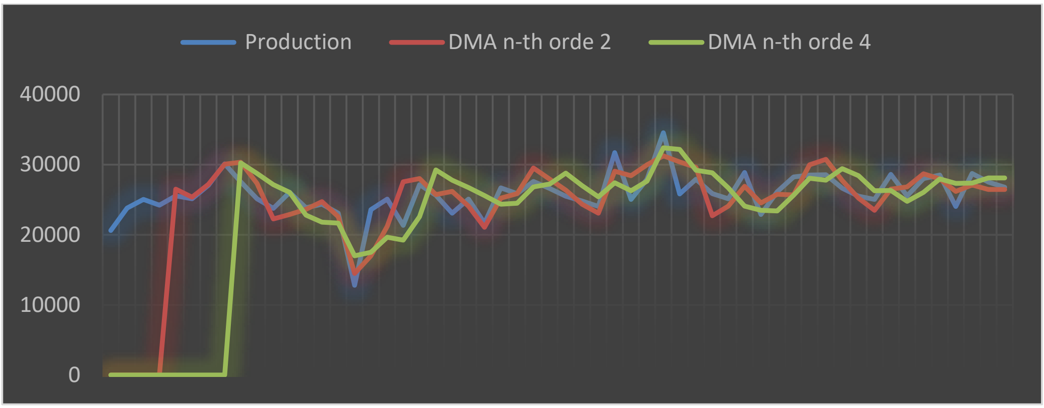

Figure 2. Trend forecasting based DMA n-th ordo 2 and 4 on Roof tile Production

To deepen the analysis of forecasting based on SMA, DMA n-th ordo 2 and 4, a combination of the results from SMA, DMA n-th ordo 2 and 4 is carried out in the form of a trend graph so that it is visible which method is more inclined towards actual roof tile production, accompanied by the results The MAPE obtained from the n-th DMA of ordo 2 is the appropriate method for forecasting roof tile production. The trend graph of production with forecasting is shown in Figure 3, and the accuracy and MAPE results of each method used are shown in Figure 4.

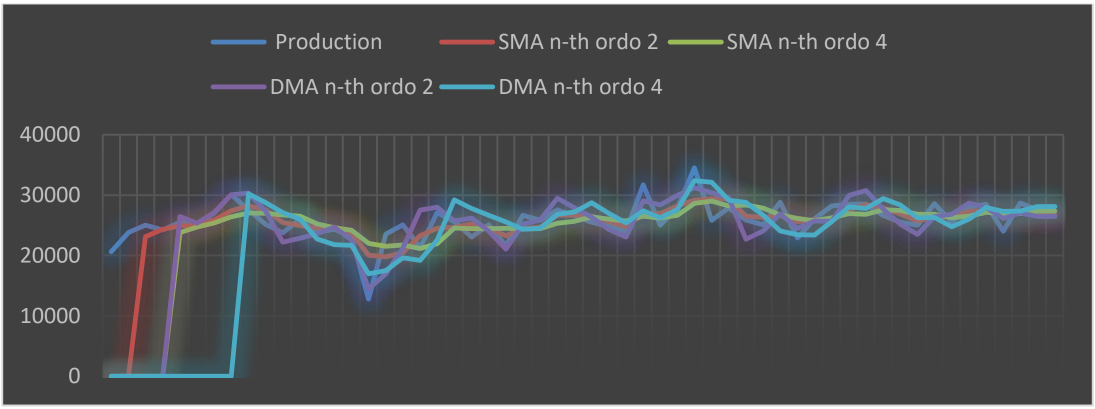

Figure 3. Trend forecasting SMA, DMA at n-th ordo 2 and 4 on Roof tile Production

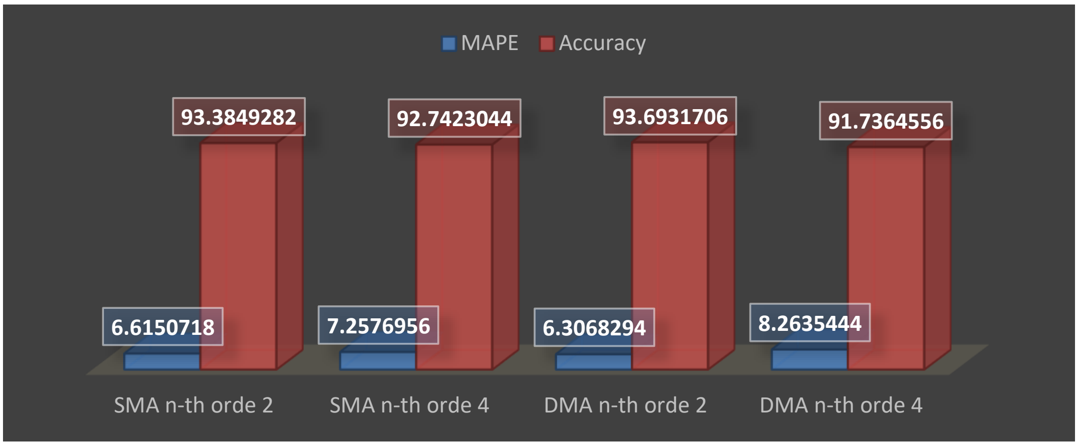

Figure 4. Accuracy and MAPE of SMA, DMA at n-th ordo 2 and 4 on Roof tile Production

D. CONCLUSION AND SUGGESTIONS

Based on the results of trials and analysis regarding the comparison of the SMA and DMA methods for forecasting roof tile production. It can be concluded that the best method for predicting this data shows that the DMA method is more precise than SMA. The test results with the best MAPE on DMA using the n-th ordo 2 parameters were 6.3%, resulting in an accuracy of 93.7%. Meanwhile, the test results using the SMA method with n-th ordo 2 parameters were 6.6%, meaning an accuracy of 93.4% was obtained. Compared with the n-th ordo 4 test results, DMA has a MAPE value of 8.2%, while SMA has a MAPE value of 7.2%. To increase forecast accuracy, this research will continue by trying other methods and increasing the amount of training data and n-th ordo variants.

REFERENCES

Alex, M. A. H., & Nur Rahmawati. (2023). Application of the Single Moving Average, Weighted Moving Average and Exponential Smoothing Methods For Forecasting Demand At Boy Delivery. *Tibuana*, *6*(1), 32–37. https://doi.org/10.36456/tibuana.6.1.6442.32-37

Astuti, Y., Novianti, B., Hidayat, T., & Maulina, D. (2019). Penerapan Metode Single Moving Average Untuk Peramalan Penjuaan Mainan Anak. *Seminar Nasional Sistem Informasi Dan Teknik Informatika Sensitif*, *4*(July), 255. https://ejurnal.dipanegara.ac.id/index.php/sensitif/article/view/552

Bhuyan, H., Kol, M., A. Adediran, D., Oluwaseyi Jessy, B., & Tundo, T. (2023). Predicting Uterine Fibroids with Multiple Classifiers: An Analysis. *SciWaveBulletin*, *01*(02), 18–26. https://doi.org/10.61925/swb.2023.1203

Dewi, E. N. S., & Chamid, A. A. (2019). Implementation of Single Moving Average Methods For Sales Forecasting Of Bag In Convection Tas Loram Kulon. *Jurnal Transformatika*, *16*(2), 113. https://doi.org/10.26623/transformatika.v16i2.1047

Eko siswanto, Eka Satria Wibawa, & Mustofa, Z. (2021). Implementasi Aplikasi Sistem Peramalan Persedian Barang Menggunakan Metode Single Moving Average Berbasis Web. *Elkom : Jurnal Elektronika Dan Komputer*, *14*(2), 224–233. https://doi.org/10.51903/elkom.v14i2.515

Febrian, D., Idrus, S. I. Al, & Nainggolan, D. A. J. (2020). The Comparison of Double Moving Average and Double Exponential Smoothing Methods in Forecasting the Number of Foreign Tourists Coming to North Sumatera. *Journal of Physics: Conference Series*, *1462*(1). https://doi.org/10.1088/1742-6596/1462/1/012046

Hudiyanti, C. V., Bachtiar, F. A., & Setiawan, B. D. (2019). Perbandingan Double Moving Average dan Double Exponential Smoothing untuk Peramalan Jumlah Kedatangan Wisatawan Mancanegara di Bandara Ngurah Rai. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *3*(3), 2667–2672. https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/4791

Khairina, D. M., Khairunnisa, R., Hatta, H. R., & Maharani, S. (2021). Comparison of the trend moment and double moving average methods for forecasting the number of dengue hemorrhagic fever patients. *Bulletin of Electrical Engineering and Informatics*, *10*(2), 978–987. https://doi.org/10.11591/eei.v10i2.2711

Khan, I., & Ahmad, A. R. (2019). Tracking Student Performance in Introductory Programming by Means of Machine Learning. In *2019 4th MEC International Conference on Big Data and Smart City (ICBDSC)* (pp. 1–6). IEEE. https://doi.org/10.1109/ICBDSC.2019.8645608

Maknunah, J. (2019). Analisis Perbandingan Double Moving Average dan Holt's Model Penerimaan Anggota Baru Koperasi "SBW" Jawa Timur. *Jurnal Ilmiah Komputasi*, *18*(4). https://doi.org/10.32409/jikstik.18.4.2656

Mustapa, R., Latief, M., & Rohandi, M. (2019). Double moving average method for predicting the number of patients with dengue fever in Gorontalo City. *Sciences and Technology (GCSST)*, *2*, 332–337. Retrieved from https://series.gci.or.id

Ogundare, O., & Wiggins, N. (2018). Identifying Sub-documents in a Composite Scanned Document Using Naive Bayes, Levenshtein Distance and Domain Driven Knowledge Base. In *5th International Conference on Soft Computing and Machine Intelligence, ISCMI 2018* (pp. 84–87). IEEE. https://doi.org/10.1109/ISCMI.2018.8703245

Rahat, A. M., Kahir, A., Kaisar, A., & Masum, M. (2019). Comparison of Naive Bayes and SVM Algorithm based on Sentiment Analysis Using Review Dataset. In *8th International Conference on System Modeling & Advancement in Research Trends* (pp. 266–270). IEEE Xplore. https://doi.org/10.1109/SMART46866.2019.9117512

Rahmalia, D. (2021). Optimizing the Membership Degree of Fuzzy Inference System (FIS) and Fuzzy Clustering Means (FCM) in Weather Data Using Firefly Algorithm. *Jurnal Matematika Murni Dan Aplikasi*, *6*(4), 169–180. https://doi.org/10.18860/ca.v6i4.8933

Riki, S. et al. (2020). Pengendalian Persediaan Dengan Metode Forcasting : Moving Average dan Exponential Smoothing. *Algor*, *2*(1), 22.

Saifullah, S., Suryotomo, A. P., Dreżewski, R., Tanone, R., & Tundo. (2023). *Optimizing Brain Tumor Segmentation Through CNN U-Net with CLAHE-HE Image Enhancement. 1st International Conference on Advanced Informatics and Intelligent Information Systems (ICAI3S 2023)*. Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-366-5

Selvachandran, G., Quek, S. G., Thi, L., Lan, H., Son, L. H., Giang, N. L., & Ding, W. (2019). A New Design of Mamdani Complex Fuzzy Inference System for Multi-attribute Decision Making Problems. *IEEE Transactions on Fuzzy Systems*, *PP*(c), 1. https://doi.org/10.1109/TFUZZ.2019.2961350

Singh, G. (2019). Comparison between Multinomial and Bernoulli Naïve Bayes for Text Classification. *2019 International Conference on Automation, Computational and Technology Management (ICACTM)*, 593–596. https://doi.org/10.1109/ICACTM.2019.8776800

Sutopo, J., Khanapi, M., Ghani, A., Burhanuddin, M. A., Septianti, A. N., & Tundo, T. (2023). Dance Gesture Recognition Using Laban Movement Analysis with J48 Classification. *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, *11*(2), 528–536. https://doi.org/10.52549/ijeei.v11i2.4314

Syahdan, S., Arif, A., & Megawati, M. (2022). Analysis of the Factors that Cause Dengue Hemorrhagic Fever (DHF) Using Chi-Square Automatic Interaction Detection (CHAID). *International Journal of Natural Science and Engineering*, *5*(3), 104–113. https://doi.org/10.23887/ijnse.v5i3.41123

Tobing, D. N. L. (2022). Indihome Product Sales Forecasting with the Double Moving Average and Double Exponential Smoothing Methods on PT. Telkom Witel Sumut Pematang Siantar. *Formosa Journal of Science and Technology*, *1*(8), 1201–1222. https://doi.org/10.55927/fjst.v1i8.2281

Tripathi, A., Yadav, S., & Rajan, R. (2019). Naive Bayes Classification Model for the Student Performance Prediction. *2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies, ICICICT 2019*, 1548–1553. https://doi.org/10.1109/ICICICT46008.2019.8993237

Tundo, T. (2022). Subjectivity Tracking System for Poor Scholarship Recipients at Elementary School Using the MOORA Method. *JTAM (Jurnal Teori Dan Aplikasi Matematika)*, *6*(3), 498–510. https://doi.org/10.31764/jtam.v6i3.8373

Tundo, T., & Mahardika, F. (2023). Fuzzy Inference System Tsukamoto – Decision Tree C 4 . 5 in Predicting the Amount of Roof Tile Production in Kebumen. *JTAM (Jurnal Teori Dan Aplikasi*

Matematika), *7*(2), 533–544. https://doi.org/10.31764/jtam.v7i2.13034

Tundo, T., & Sela, E. I. (2018). Application of The Fuzzy Inference System Method to Predict The Number of Weaving Fabric Production. *IJID (International Journal on Informatics for Development)*, *7*(1), 19. https://doi.org/10.14421/ijid.2018.07105

Tundo, & Uyun, S. (2020). Penerapan Decision Tree J48 Dan Reptree Dalam Menentukan Prediksi Produksi Minyak Kelapa Sawit Menggunakan Metode Fuzzy Tsukamoto. *Jurnal Teknologi Informasi Dan Ilmu Komputer (JTIIK)*, *7*(3), 483–492. https://doi.org/10.25126/jtiik.202071870

Wang, W. H., Urbina, A. N., Chang, M. R., Assavalapsakul, W., Lu, P. L., Chen, Y. H., & Wang, S. F. (2020). Dengue hemorrhagic fever – A systemic literature review of current perspectives on pathogenesis, prevention and control. *Journal of Microbiology, Immunology and Infection*, *53*(6), 963–978. https://doi.org/10.1016/j.jmii.2020.03.007

Weerathunga, P. R., Xiaofang, C., & Sameera, T. K. G. (2020). Heterogeneity in Earning Management of Listed Companies Following International Financial Reporting Standards Convergence: a Developing Country Experiences. *International Journal of Economics and Financial Issues*, *10*(1), 101–108. https://doi.org/10.32479/ijefi.8872