Forecasting Model of Corn Commodity Productivity in Indonesia: Production and Operations Management, Quantitative Method (POM-QM) Software

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***Abstract*—Food is an essential ingredient needed by humans. In addition to being consumed, it can also be a valuable commodity for economic purposes through productivity of food crops. Therefore, this study aims to model the forecasting of maize productivity in Indonesia using Production and Operations Management-Quantitative Method (POM-QM) software. The data collected on productivity of corn commodities in Indonesia between 1980-2019 shows fluctuations, with both deficit and surplus periods. This study uses a time series data-based forecasting model consisting of three methods, namely Double Moving Average (DMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES). The selection of the best model was conducted based on the Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percent Error (MAPE). SES emerged as the most preferred, with a lower MAPE value of 4.913%. The predicted productivity of corn in Indonesia is estimated at 5.28 tons/ha/year, sufficient to meet consumers' demand. Therefore, governments are recommended to use this information in predicting corn productivity to meet the national demand in the future.**

Keywords*—*Forecasting model; productivity; corn commodity; POM-QM

I. Introduction

Food security is a vital issue in Indonesia. Furthermore, it is essential to make sufficient food available to meet the population's needs, to avoid prolonged political and social turmoil. Food security is also an indicator of a country's economic growth and can reflect prosperity and a benchmark for the level of welfare, especially in terms of people's productivity and consumption [1]. Therefore, to optimize the utilization of natural resources in each region, it is imperative to implement management strategies tailored to each region's unique characteristics [2-6].

The government's commitment to addressing food security is evidenced by recognizing food as a human right for Indonesian citizens, as stipulated in Law Number 18 of 2012. This aligns with the first and second goals of the Sustainable Development Goals (SDGs), which aim to end poverty worldwide and achieve food security and improved nutrition while promoting sustainable agriculture.

The commodity corn (Zea mays L.) is an alternative staple food and a grain plant from the grass family (Graminaceae). In Indonesia, the main maize-producing regions include Central Java, West Java, East Java, Madura, Special Region of Yogyakarta, East Nusa Tenggara, North Sulawesi, South Sulawesi, and Maluku. Especially in East Java and Madura, corn plants are cultivated intensively due to the favorable soil and climate conditions that support their growth [7].

Corn is a food commodity that plays an essential and strategic role in national development [8], and its contribution to the Gross Domestic Product (GDP) continues to increase yearly, even during an economic crisis [9]. It is one of the most important staple foods in Indonesia. Furthermore, this crop, alongside two other commodities, namely rice and soybeans, is the main target of the Ministry of Agriculture in achieving food self-sufficiency.

Corn is also widely used for multiple purposes, including as a food and feed ingredient. It is being adopted as an alternative fuel source domestically and internationally [8]. However, the demand for this crop remains high since it serves as an ingredient for animal feed companies and other food processing industries [10]. The Ministry of Agriculture considers five commodities such as corn, rice, soybeans, sugar, and beef, as the main food items [11].

As the second most produced food after rice, corn's high demand as animal feed and for industrial purposes poses challenges such as depletion of natural resources and the impact of climate change. Cooperation and collaboration are required to support the development of sustainable corn commodities [12]. However, the problem of land-carrying capacity is a constraint for Indonesian agriculture. As the population increases, more land is needed to meet housing demands, leading to the conversion of agricultural land and affecting corn productivity in the country. Despite a fluctuating rise in production in Indonesia between 1980 and 2019, the overall increase was only 3.98 tons/ha/year or 0.102% per year [11]. There are high fluctuations in productivity of corn commodities. This fluctuation is attributed to internal and external factors such as climate, weather, and government policies.

Thirty years ago, maize was primarily consumed as food. However, with the development of the poultry industry in the early 1970s, corn began to be used as an energy source for modern poultry feed [13]. Before 1990, it was shown that 86% of this crop in Indonesia was consumed directly, and only about 6% was used in the feed industry. Despite this, the adoption of maize in the food industry remains low, accounting for only 7.5% [6]. The availability of this commodity is wider in the rainy than dry season [14]. This crop is typically cultivated on dry land and planted during the rainy season. The limited harvest area during the dry season results in the low availability of corn to meet the domestic industry's needs [9].

According to Purwanto [14], from 1989-2002, there was a shift in the use of maize, with a continued dominance for direct consumption. After 2002, a greater proportion was employed to meet the demand of the feed industry. The use of this commodity in the food industry has also been on the rise. This change has transformed maize from a staple food commodity into an industrial raw material [15]. The demand for the commodity continues to grow yearly with the increasing population and industry [14]. Additionally, rising oil prices also impact its dynamic demand. The increase in the use of maize as an alternative energy and raw material for the feed and food industries is expected to persist. Furthermore, the rise in per capita income causes an increase in demand for corn commodity derivative products [9].

Forecasting involves estimating future requirements, including the quality of goods, time, and location needed to meet demand [16]. It is the art and science of predicting events yet to occur by always using data from the past [17-18]. According to [19-20], as a crucial component of decision-making, forecasting requires predicting future events to inform effective decisions. Inaccurate forecasting results pose a persistent challenge [16].

Time series analysis and forecasting are active study areas [21]. The accuracy of time series forecasting plays a crucial role in the decision-making process. The several method used in prediction include the time series method, which is grouped into the average (Single Moving Average (SMA) and Double Moving Average (DMA)), the smoothing (Single Exponential Smoothing (SES), double exponential smoothing from Brown and Holt), and the regression method, namely time series regression [22-23-24].

Method used in forecasting vary widely but are adapted to the pattern of data. Generally, there are three types of method to determining the level of the error. These include MAD, MSE, and MAPE, which calculate the average absolute difference, average difference in rank, and average absolute difference percentage, respectively [25]. In utilizing the time series method, it is important to identify the data pattern type, which includes trend, cyclical, seasonal, and horizontal [26].

The availability of several statistical softwares supports the selection of forecasting method. Various study analysts have conducted forecasting models using software assistance to facilitate calculations [27]. For instance, POM-QM software has been studied for product sales forecasting [28]. Furthermore, this method provides module options for mathematical calculations. Its forecasting model has several method, including Naive, Moving Average, Weighted Moving Average (WMA), Exponential Smoothing, Trend Analysis (regression over time), Linear Regression/Least Square, Multiplicative Decomposition (seasonal), and Additive Decomposition (seasonal). Given these considerations, it is necessary to have a model to predict productivity of corn commodities. Therefore, this study aims to establish a forecasting model for corn commodity productivity in Indonesia using Production and Operation Management-Quantitative Method (POM-QM) software.

II. Materials and Method

The variable used was the harvested area of corn per year from 1980-2019. Secondary data in the form of time series sourced from the data and information center (Pusdatin) under the Ministry of Agriculture and the Central Bureau of Statistics (BPS) were used in this study. The population consists of information on productivity of corn commodities from 1980-2019. A saturated sampling method was employed, where all population members were used as samples.

Forecasting model for corn commodity productivity in Indonesia:

A. *Forecasting Model of Corn Commodity Productivity with DMA*

Double-moving average is used to forecast time series data with a linear trend [26]. Multiple moving averages, also known as linear moving averages, deal with time series data with patterns that tend to experience a linear trend. Furthermore, the double-moving average is a method that simultaneously uses single-moving average data with adjustments between the first and second moving averages and trend adjustments [29].

DMA is a method in which the first and second moving average groups are calculated. It is symbolized by ($k \times k$), meaning that the moving average is calculated using the k periods [23]. The moving average method has no objective basis for determining the number of moving average orders [30].

Many methods can be used in forecasting, including DMA. The data used for calculations do not have elements of trend or seasonal factors. DMA is a forecasting method performed on past data for two periods with an average pattern [31], which is suitable for long-term data [32]. The mathematical equation of DMA is presented in Equation 1:

$$F_{t+1} = \frac{X_1 + X_2 + \ldots\ldots\ X_T}{T} \quad (1)$$

Information:

F_{t+1} = Forecast for period t+1

X_T = True value of t period

T = Timeframe of moving average

The process data analysis in forecasting model for corn commodity productivity using DMA involve several steps, including (a) identify time series data patterns, (b) determine the value of the first moving average, (c) determine the value of the second moving average, (d) determine the value of the constant (at), (e) determine the value of the trend coefficient (bt), (f) select the best model based on the criteria for forecasting accuracy, and (g) determine forecast results for future periods. The data analysis was performed using the help of POM-QM software to facilitate the computation process.

B. Forecasting Model of Corn Commodity Productivity with WMA

WMA forecasting method develops the moving average method with additional weights in the calculation. It is calculated by assigning greater influence to certain values in a data set based on their attributes. In contrast, the average is determined by giving weights. WMA forecasting method is an advanced version of the moving average method in which each time series is given a certain and different weight [33]. In simple terms, WMA is a moving average given weight in each data [34].

Determination of weight is subjective, depending on the experience and opinion of the data analyst. For instance, the analyst may give more weight to the last observation or vice versa. The weighted factor will be greater in the final period than in the early period when the weighting opportunity is higher in the previous observation. The longer the period specified, the greater the weighting given to the most recent data, and the number of weighted opportunities equals one [35]. Finally, the formula used in forecasting model of corn commodity productivity with WMA is presented in Equation 2.

$$WMA_{t+1} = kX_1 + (k-1)X_{t-1} + \dots + X_{t-(n-1))} / k + (k-1) + \dots + 1 \quad (2)$$

Information:

k number of periods or ranges of forecasting numbers,

X_t is the time series data value at point t.

C. Forecasting Model for Corn Commodity Productivity with SES

SES is a simple method that requires estimating a single parameter. It assigns Exponential Moving Average (EMA) weights to all historical data. The exponential smoothing forecasting method is an iterative procedure of repeating calculations that improves the forecast (smoothing) by calculating the average of past values in a time series in an exponential manner [36-37-38]. SES is appropriate for data without extreme trends and is usually for forecasting one period in the future. The goal is to estimate the current level and use it to forecast preceding values. Forecasting model for corn productivity with SES employs the formula in equation 3 [39].

$$F_{t+1} = \alpha . X_t + (1 - \alpha)\ F_t \quad (3)$$

Information:

Ft+1 is the forecast for the next period, α is the smoothing constant, Xt is the t-th data or observation, and Ft is the t-th period data. The Ft+1 forecast is based on the weighting of the latest Xt data with a weight of α and the newest forecasting weighting of Ft with a weight of 1-α. By repeating this process and replacing Ft+1 and Ft+2 with their components, the result in Equation 4 is obtained:

$$F_{t+1} = \alpha . X_t + (1 - \alpha)\ F_t \quad (4)$$

$$= \alpha . X_t + (1 - \alpha)[\ \alpha\ .X_{t+1} + (1 - \alpha)\ F_{t+1}\ ]$$

$$= \alpha . X_t + \alpha(1 - \alpha) X_{t+1} + (1 - \alpha)^2\ F_{t+1}$$

$$= \alpha . X_t + \alpha(1 - \alpha) X_{t+1} + \alpha(1 - \alpha)^2\ F_{t+1}$$

Therefore, Ft+1 is WMA of all historical data. As t increases, the value of (1–α)2 decreases, leading to a smaller contribution from F(1). Since F1 is not known, the initial value can be estimated. For volatile initial data, one method is to set the first forecast equal to the first observation, F1=y1. Furthermore, for initial data that is quite constant, the average of the first five or six data points can be used as the first forecast F1=MA(5) or F1=MA(6). The exponential smoothing equation can be rewritten in a form that describes the role of the weighting factor α, as shown in Equation 5:

$$Ft+1 = Ft + \alpha(X1 - Ft) \quad (5)$$

Exponential smoothing is used to adjust a previous forecast (Ft) by incorporating adjustments for errors. The value of α, which ranges between 0 and 1, cannot be equal to 0 or 1. To obtain a stable forecast with random smoothing, a small α value should be used for data that does not fluctuate too much. In contrast, a large α value is more appropriate for data that fluctuates significantly and requires a fast response to changes. To determine the optimal α value, one can estimate it using trial and error, testing values of 0.1, 0.2, 0.3, ..., 0.9, and selecting the value with the smallest MSE for the next forecast.

Selection of the best model for forecasting productivity of corn commodities

The accuracy of calculations in the forecasting method is often subject to variations in data patterns. Therefore, selecting the right method is imperative to minimize errors in the forecasting results [40]. Each method has its level of accuracy that needs to be considered. As a result, it is essential to choose a method that can minimize forecasting errors. According to [41-42], forecast facts are expected to have small values and errors. The error value is inversely proportional to the accuracy of the prediction result.

The selection of the best forecasting model depends on the resulting error. Some of the criteria that are often used to calculate the accuracy of the model forecasting time series include: (a) Mean Absolute Deviation (MAD), (b) Mean Square Error (MSE), and (c) Mean Absolute Percent Error (MAPE). The smaller the criterion value, the better the prediction results obtained [43-45].

1) MAD: Method for determining the overall forecast error is MAD, which is obtained by dividing the sum of the absolute values of each error by the sample size (number of forecast periods) [43-44]. Finally, the mathematical formula of MAD is presented in Equation 6:

$$MAD = \frac{\sum_t^n \ (At\_Ft)}{n} \quad (6)$$

information:

A_t = Actual demand in period t

F_t = Forecasting demand in period t

n = Number of forecasting periods involved

2) MSE: MSE is calculated by adding the squares of all errors in each period and dividing them by the number of forecasting periods [43-44]. The mathematical expression of MSE is presented in Equation 7:

$$\text{MSE} \quad = \sum_t^n |At - Ft|^2 \tag{7}$$

Information:

A_t = Actual demand in period t

F_t = Forecasting demand in period t

n = Number of forecasting periods involved

3) MAPE: MAPE is an evaluation calculation used to measure the accuracy of prediction [45-46-47]. It [48-49] was chosen as the performance metric and was employed to assess forecasting method accurately. Furthermore, MAPE is not influenced by the predicted time series magnitude [50-51]. Also, it is frequently used in practice [52], independent of scale, and easy to interpret, which makes it popular among industry practitioners [53-54]. MAPE measures the average of absolute errors as a percentage of the average absolute error rate of the actual data period. The mathematical expression is shown in Equation 8:

$$MAPE = \frac{(100)}{n} \sum_t^n \frac{(At\_Ft)}{|m|} \tag{8}$$

Information:

A_t = Actual demand in period t

F_t = Forecasting demand in period t

n = Number of forecasting periods involved

MAPE measures the average of absolute errors as a percentage of the average value total error rate of the actual data period. Its criteria explain that the smaller the MAPE value, the better the accuracy. Table I shows the score criteria [55].

TABLE I. MAPE VALUE CRITERIA

MAPE value	Criteria
< 10	Very good
10 - 20	Well
20 - 50	Enough
>50	Bad

Productivity data processing of corn commodities is carried out using POM-QM software.

The subsequent stage involves describing and processing data on productivity of corn commodities. The POM-QM software application was employed to process corn commodity productivity data from 1980-2019. Several forecasting method in the POM-QM application were utilized, resulting in the generation of anticipated forecast outcomes.

To apply the POM-QM software in forecasting productivity of corn commodities, the steps to be followed include: (a) run the QM program and select the module-forecasting; (b) select the menu File-New-Time series Analysis and a dialogue box titled "Create data set for Forecasting/Time-series Analysis" will appear (c) in the dialog box, provide the title of the forecast, "Productivity of corn commodities," along with the number of time series data periods to be used as training data, starting from 1980-2019. Specify the name that will appear for each row period name, either using numbers, letters, or months. After completing the above steps, press the OK button. The data settings in QM for Windows are shown in Fig. 1.

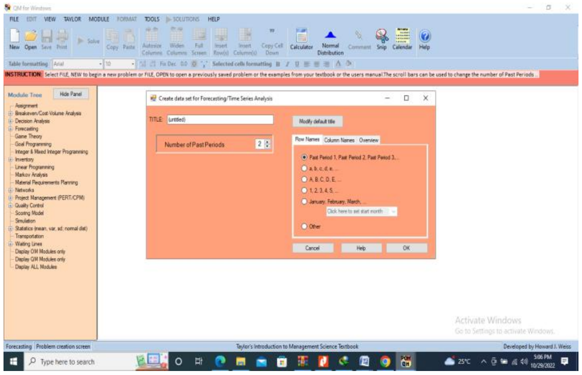

Fig. 1. Data settings in QM for windows.

Forecasting is crucial for companies as it aids in managing productivity, inventory, and planning decisions [56]. According to [57], relying on a single forecasting model is insufficient. Several choices of forecasting models should be considered to arrive at the most accurate prediction. The forecasting results for productivity of corn from each method are then collected and analyzed for accuracy. Therefore, it is important to choose the appropriate forecasting method, as using an inappropriate one may reduce the forecast's accuracy.

III. RESULTS AND DISCUSSION

A. *Forecasting Model of Corn Commodity Productivity with DMA*

DMA is a forecasting method conducted by adding corn commodity productivity data in the two previous periods and dividing the sum by two. It can also be performed by calculating the average of corn commodity productivity data in the two previous periods. The results of moving average forecasting are shown in Table II.

TABLE II. CALCULATION OF THE DOUBLE MOVING AVERAGE FORECAST AT CORN COMMODITY PRODUCTIVITY

Measure	Value
Error Measures	
Bias (Mean Error)	.154
MAD (Mean Absolute Deviation)	.154
MSE (Mean Squared Error)	.037
Standard Error (denom=n-2=35)	.199
MAPE (Mean Absolute Percent Error)	4.913%
Forecast	
next period	5.28

Based on DMA applied to forecast corn commodity productivity, Table II presents the results of the bias or average error, which are 0.154. MAD is also 0.154, while MSE (Mean Squared Error) is 0.037. Fig. 2 shows the forecasting graph of productivity of corn commodities using this method.

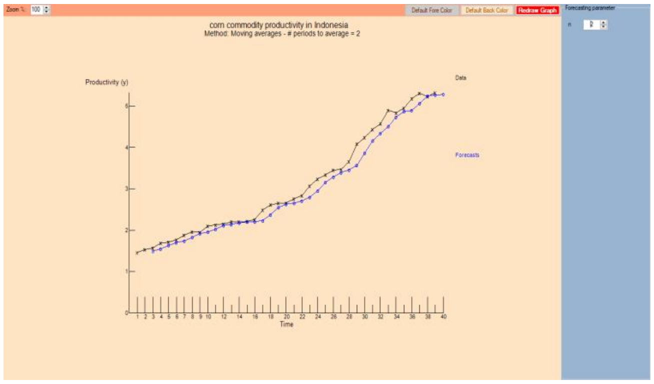

Fig. 2. Forecasting graph with the double moving average method on productivity commodity corn.

Fig. 2 shows that the forecasting results for corn commodity productivity from DMA appear different from the actual data. This is because the standard error of this method is 0.199 deviations.

B. *Forecasting Model for Productivity of Corn Commodity with WMA*

WMA 2 is performed by assigning weight to corn commodity productivity data for the last two years. The forecasting of corn commodity productivity began in 1980-2019. The calculation process of this forecasting method is presented in Table III.

TABLE III. FORECASTING THE WEIGHTED MOVING AVERAGE ON PRODUCTIVITY COMMODITY CORN

Measure	**Value**
Error Measures	
Bias (Mean Error)	.205
MAD (Mean Absolute Deviation)	.205
MSE (Mean Squared Error)	.065
Standard Error (denom=n-2=35)	.261
MAPE (Mean Absolute Percent Error)	6.517%
Forecast	
next period	5.23

Based on WMA applied to forecast corn commodity productivity, Table III present the results of the bias or average error, which are are 0.205. MAD is also 0.205, while MSE is 0.65. Fig. 3 shows the forecasting Graph with WMA for productivity of corn commodities.

According to Fig. 3, the forecasting results for corn commodity productivity using WMA display a slight increase towards the end of the period in comparison to DMA. However, it should be noted that this increase is attributed to the standard error of 0.261 deviation, as evidenced by the actual data.

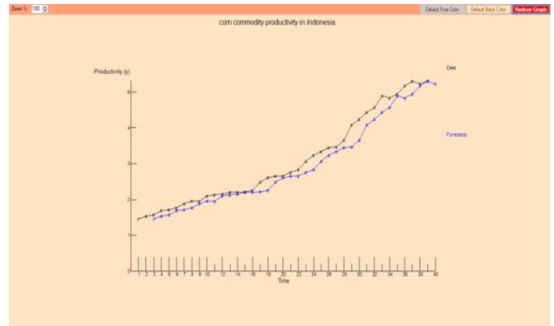

Fig. 3. Forecasting graph with the weighted moving average method at corn commodity productivity.

C. *Forecasting Model of Corn Commodity Productivity with SES*

To calculate the forecasting of corn commodity productivity using SES, the α coefficient is first determined. This is performed by multiplying α by the actual demand. Afterwards, the result is added with the outcome of 1 minus α multiplied by corn commodity productivity forecast in the previous period. The value of α is assumed to be 0.5 in this model. The forecasting process using SES is presented in Table IV.

TABLE IV. FORECASTING SINGLE EXPONENTIAL SMOOTHING AT CORN COMMODITY PRODUCTIVITY

Measure	**Value**
Error Measures	
Bias (Mean Error)	.2
MAD (Mean Absolute Deviation)	.2
MSE (Mean Squared Error)	.056
Standard Error (denom=n-2=36)	.244
MAPE (Mean Absolute Percent Error)	6.356%
Forecast	
next period	5.263

Table IV shows that from the results of forecasting productivity of corn commodities using SES, the bias or average error of this forecast are 0.2. MAD is also 0.2, while MSE is 0.056. Fig. 4 shows the forecasting Graph of SES.

Fig. 4 shows that the forecasting results for corn commodity productivity from WMA appears to be more stable than SES. This is because the standard error of this method is 0.244 deviations.

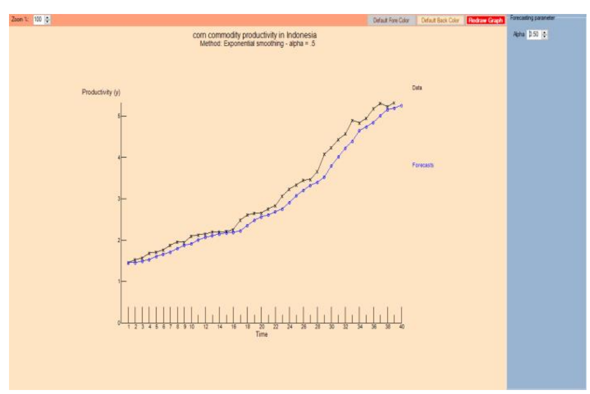

Fig. 4. Forecasting graph with the single exponential smoothing method on corn commodity productivity.

Table V presents the forecasted corn commodity productivity using method such as (a) DMA, (b) WMA, and (c) SES in the next (year). The data used in the analysis consist of 39 years productivity, spanning from 1980-2019.

TABLE V. THE VALUE OF THE SIZE OF THE ERROR IN THE FORECASTING MODEL FOR THE PRODUCTIVITY OF CORN COMMODITIES

Method	Value Measurement Error			
	MAD	MSE	SEE	MAPE
Double Moving Average	0.154	0.037	0.199	4.913%
Weighted Moving Average	0.205	0.065	0.261	6.517%
Singel Exponential Smooting	0.2	0.056	0.244	6.356%

The analysis in Table V compares the error rates of the three different methods for forecasting corn productivity. Based on the results, DMA outperforms the other method with an MAPE value of 4.913%, which is very close to zero. Therefore, DMA is chosen for forecasting corn commodity productivity. The forecasting values for the upcoming period are presented in Table VI.

TABLE VI. VALUE OF CORN COMMODITY PRODUCTIVITY FORECASTING SIZE NEXT PERIOD

Method	Forecasting Next Period's Measurement Value
Double Moving Average	5.28
Weighted Moving Average	5.23
Singel Exponential Smooting	5.263

Table VI indicates that the forecasted corn commodity productivity for the next period is 5.28 tons/ha/year. This implies that corn commodity production in Indonesia is expected to satisfy the entire consumer demand.

IV. CONCLUSIONS

Forecasting results of corn commodity productivity, using the following methods: (a) Double Moving Average, (b) Weighted Moving Average, and (c) Single Exponential Smoothing in the next (year), from 1980 – 2019: Forecasting model for corn commodity productivity The selected method, namely the Single Exponential Smoothing method, has a lower error rate than other forecasting models, the MAPE value is 4.913%. The forecasting model for corn commodity productivity is 5.28 ton/ha/year, meaning that corn commodity productivity in Indonesia is expected to meet all consumer demands for corn commodities. The results of this study are expected to assist the government in predicting the amount of corn commodity productivity in the next period by national corn needs.

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