Analyzing the Importance of Electronic Data Capture (EDC) for Sales Volume Prediction at Bank Merchants with the Arima Method

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ABSTRACT

Payments with Electronic Data Capture (EDC) are becoming increasingly attractive to banks due to their efficiency, convenience and potential for data-based insights. The study aims to explore the use of transaction data from debit and credit cards at one of the largest banks in Indonesia to predict following year's sales volume and growth using the Autoregressive Integrated Moving Average (ARIMA) method. Historical data on debit card and credit card transactions based on a predictive model using the ARIMA method was generated. The purpose of this study was to forecast sales volumes for the following year and identify potential growth patterns. Data preprocessing, model selection, and evaluation to ensure robust and accurate predictions as the methodology is used. The output of this study in the form of predictions for the following year can be used by banks EDC machines issuers in designing business plans in order to increase sales transactions. For further research, the results of this study can be used to measure the gap between forecasting results and actual results.

Keywords: Prediction, Electronic Data Capture, Arima, Forecasting, Sales Volume.

INTRODUCTION

Currently, payment methods for buying and selling transactions are very diverse, especially due to developments in digital technology that have occurred in the last decade. One method of payment that has been around for a long time and is still frequently used today is payment using an EDC (Electronic Data Capture) machine. This machine is usually used for payments using credit cards, debit cards, QR Codes, or other payments under the UPI (Unified Payment Interface) system. When choosing a payment system, consumers not only ask for convenience in transactions, but they also need an assurance the data confidentiality and a security in every transaction.

The use of EDC is supporting a transaction security for business owners (merchants) in terms of reducing the risk of fraud transactions and financial bookkeeping. For consumers, transactions via EDC machines make payments easier, especially for large transaction amounts. Based on data from the Indonesia's central bank, electronic money payments increase by 30% in 2022, which is due to the growth of e-commerce business. This growth also resulted in significant growth in digital banking transactions, reaching 28.7% or worth IDR 52,545.8 trillion. The increase in EDC usage also for conventional payments such as using debit cards which is increase by 20.7%, and credit cards payment increase even higher, i.e.: 31.7%. With this growth, sellers or merchants need to maintain their sales using EDC. They need to estimate and plan a sales strategy that using EDC for their business transactions. Based on this reason, this research focuses on predicting transactions at merchants who use EDC machines [1].

In this context, the use of EDC has a significant impact on transactions and sales volume. Number of transactions and Sales Volume are two important indicators that describe sellers' business activities. Therefore, it is important to analyze historical transaction data to predict future Sales Volume. Despite the crucial role of EDC in economic activity, there has not been much research or studies that specifically look at its impact on payments using EDC. Hence the outcome of this research is important for merchants who use EDC in order to predict their business growth. Data analysis and Sales Volume predictions can provide valuable insights for decision making at both individual and organizational levels, as well as enabling the development of more effective strategies in optimizing EDC utilization.

Predicting future value is important in business planning and decision making. Historical data is used to understand past trends and use them to predict the future. These predictions help in changing business behavior and strategies to achieve better goals. How we respond to predicted changes is very important in making business decisions. This study aim is to find out the sales potential for the next following year, to indicate and analyze the growth of transactions from EDC over the next following year. The data were collected from bank EDC merchant This forecast is based on the data at Bank EDC Merchants as banks that issue EDC machines.

LITERATURE REVIEW

With the continued development of technology, particularly digital technology, it has disrupted almost all business sectors and business processes. In terms of payment methods, the presence of digital technology has given sellers and buyers options in executing payment transactions. Sellers can choose the payment transaction method that is most profitable for their business. Meanwhile, on the other hand, buyers can determine the most comfortable, safe and reliable payment method. Which is more profitable for merchants, cash transactions or payment with debit cards, has different answers in several countries and is still being debated [2]. Each consumer has different preferences in choosing payment methods, which are influenced by socio-economic factors and the habits of each individual consumer [3], [4].

Survey reveal that the selection of payment method can also be based on the size of the transaction, the demographic location of the country where the transaction takes place, and even the specific location of the transaction [5]. Of the several payment methods, payment using credit cards and debit cards is still the payment method that consumers choose more than other payment methods [6], [7]. Historically, credit cards and debit cards transactions are payment methods that has been known by the customers longer and they are more familiarized with, compared to other digital payment methods [8], [9]. From this figure, it can be said that the use of EDC machines in payment transactions plays an important role. Both banks that issue EDC machines and sellers as point of sales that use EDC machine need to pay more attention on the machine reliability and marketing strategy to maintain their sales that transactions through EDC machines [10]. Transaction security of EDC machine is one of the issues that consumers concerned about in making a payment, since it is reported that error and fraud in credit cards payment is happened are quite frequently [11], [12].

One of the indicators that can be used to measure the transaction performance of a business is sales volume [13], [14]. Similarly, in measuring sales performance that occurs through EDC machines, sales volume is also used as a reference. In the case where the bank would like to design a business strategy to increase the productivity of using EDC machines at each of its merchants, then one approach that can be used is the forecasting approach [15]. This forecast is based on time series data which is then analyzed to predict future trends. There are several time series models that can be used in forecasting [16], one of the commonly used is the ARIMA model or Autoregressive Integrated Moving Average [17], [18]. The ARIMA model is widely used as a forecasting approach for several cases, including: electrical energy consumption [19], fiscal policy [20], supply chain [21], stock demand [22], and many others.

One critical aspect of business that utilizes forecasting techniques is sales, where the ability to forecast accurately can be the key to success. Recent studies highlight the importance of forecasting techniques in facing the challenges of market demand that is difficult to predict [21], [23], [24], [25]. However, given the diversity and uncertainty of data, forecasting is becoming increasingly complex, especially with limited historical data and wide variations. This is why integration of information technology (IT) or computerized systems is needed to increase the level of forecasting accuracy [21]. The application of information technology in forecasting techniques includes Machine Learning methods [26], [27] and Artificial Neural Networks [28]. There is also a combination of hybrid models[29] such as Convolutional Neural Network (CNN) with Bidirectional Long Short-Term Memory (BiLSTM) [30], [31]. The integration of this technology not only increases accuracy, but also opens up new opportunities to forecast with more precision and efficiency in facing dynamic business challenges.

RESEARCH METHODS

The research was focuses on predicting sales volume on sales transaction using EDC Merchant of the Bank. The transaction data was collected within a year 2022. The data that were collected includes information regarding transactions, sales and time, and those data will be analyzed to produce short-term forecasting within one year into the future, from June 2023 to May 2024. Because the data collected is quantitative data, this research uses a descriptive quantitative approach. The quantitative analysis in this research is based on a certain population or sample, data collection is based on the research instruments selected to test the research hypotheses that have been determined [32].

The Sales Volume of EDC Merchants is defined as the total amount of sales received by the Bank from all transactions through EDC machines at all the Bank's merchants. The data collected are the operational data which consists of several information that are required to be analysed before being used. The Sales Volume of EDC Merchants is defined as the total amount of sales received by the Bank from all transactions through EDC machines at all the Bank's merchants. The data collected are the operational data which consists of several information that are required to be scrutinized and cleaned before being used. Some data have incomplete information, hence it needs to be cleaned up. The period of data collection is during the period January 2018 to May 2023, from a total of 65 EDC merchants.

The data analysis technique uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) technique. This method is a standard framework for data mining which consists of six stages. The first stage is Business Understanding, where the researcher determines and understands the objectives of the model design and the data that will be used. The next stage is Data Understanding, which is the stage that contains analysis of the data that has been collected. Data Preparation is the third stage which focuses on preparing and refining the data to be treated. The fourth stage is constructing the Model, in this case the Autoregressive Integrated Moving Average (ARIMA) model forecasting technique was used. Evaluation is the fifth stage where the model is evaluated whether it is suitable for the current research topic. The final stage is Deployment, where the research results are applied in business.

To achieve the research objectives, time series data of chosen variables were plugged into ARIMA Model. This type of model mostly used for short-term period of forecasting, because it use historical data and impacted by human thought. There are three components of ARIMA, the first two words "*AR*" stand for autoregressive, which refers to number of lag observations or predicts future values based on past values. "*I*" stands for integrated, which indicates that it notices the variations between values from static data and previous values. Lastly "*MA*" is moving average which describes the size of the moving average window. The ARIMA model requires the assumption that data is stationary in data variations or in other words the data is consistent.

The collected data was analyzed using the Exploratory Data Analysis (EDA) technique. This technique is used to identify patterns, find anomalies, test hypotheses, and check assumptions in the data. Also, this technique can detect several errors in the data such as missing values, outliers, duplication, encodings, noisy data, or incomplete data. With this technique, we can ensure data accuracy before making assumptions and identifying errors in the data. To measure the level of accuracy of predictions made in this research, MAPE (Mean Absolute Percentage Error) calculations were used. MAPE results are used to determine the extent to which predictions are adequate. A smaller MAPE value indicates a higher level of precision.

RESULT

As written at the beginning of this paper, the object of the research is sales transactions using an Electronic Data Capture (EDC) machine. EDC is a machine that accepts payment processes from customers and is connected to merchant and customer bank accounts. The sales transaction data that were collected is monthly sales data for 65 months or the period January 2018 to May 2023. In developing a predictive model to estimate sales for the next twelve months (June 2023 to May 2024), the Python programming language was used. Several algorithms have been run with data analysis carried out to produce accurate prediction results.

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Business Understanding

As the research uses the CRISP-DM technique for data analysis, the first stage of the technique is Business Understanding. It is believed that for every transaction with the EDC device, the sales data transaction will be recorded and automatically stored in the EDC bank provider. Those data have significant value, especially in terms of accumulated funds managed by the Bank. The more transactions processed, the greater the amount of funds that will be stored in the bank.

Data Understanding

Sales volume, transaction type, transaction time, merchant information, merchant code, payment type, location (regional and branch offices), and much more are among the various details on data collected by EDC. All of the data must be arranged into a predictive model in order to make predictions. As a result, proper data classification and grouping must be carried out. For example, transaction date data is converted to year and month format, sales volume is tallied monthly, and all regional offices are consolidated into one category under an Office Name. The purpose of all of this is to make the data easier to understand for upcoming analysis.

Table 1 Edc Scraping Sales Volume Results

	Kantor	Tahun	Bulan	SV	Trx	Date
53	Indonesia	2018	1	4038981736684	3942122	2018-01-01
54	Indonesia	2018	2	3532654266289	3981766	2018-02-01
55	Indonesia	2018	3	3740675935027	4345417	2018-03-01
56	Indonesia	2018	4	3556691802928	4539429	2018-04-01
57	Indonesia	2018	5	3910876749624	4552204	2018-05-01
...	...	...	...	...	...	...
0	Indonesia	2023	1	7753476858436	13885654	2023-01-01
1	Indonesia	2023	2	7817736206757	12258429	2023-02-01
2	Indonesia	2023	3	8965558175077	13255189	2023-03-01
3	Indonesia	2023	4	8341221892362	13417306	2023-04-01
4	Indonesia	2023	5	8391310740660	12953989	2023-05-01

65 rows × 6 columns

Data Preparation

In preparing the prediction process, the Exploratory Data Analysis (EDA) is carried out. In the analysis the Sales Volume report is aggregated. Subsequently, data selection is done to make there are no data duplications and blank data.

Table 2 Missing Value Data

```
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Kantor  65 non-null     object
 1   Tahun   65 non-null     int32
 2   Bulan   65 non-null     int32
 3   SV      65 non-null     object
 4   Trx     65 non-null     int64
 5   Date    65 non-null     datetime64[ns]
dtypes: datetime64[ns](1), int32(2), int64(1), object(2)
```

Missing Value Data SV

From the Exploratory Data Analysis it shows that the p-Value = 0.044894, so it means the data is stationary, hence the prediction process can be continued.

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In preparing data for the prediction process, Exploratory Data Analysis is carried out. Analysis using correlogram graphs is to detect auto correlation, but what is measured is not between variables but between time series data and lag values over consecutive time intervals. From the graph it can be said that there tends to be no auto correlation. Meanwhile, analysis of the Standardized residual graph can be seen that the graph is not spread randomly but is around a line and does not rest on one side so that there is no residual problem. In the Histogram graph, the density plot shows a normal distribution with the average slightly shifted to the right. Lastly on the Normal Q-Q Quantiles Toerities graph, most of the red dots are perfectly distributed in line with the red colored line, any significant deviation would imply that the distribution is skewed. Based on the test results of the ARIMA model with the SARIMAX(1, 1, 0)x(0, 1, 1, 11) model types, where this model combines autoregressive (AR), moving average (MA), and seasonal differencing components, it produces Log Likelihood (LL), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) are -1520.911 ; 3047.823, and 3053.733 respectively. With a high log-likelihood value and low AIC and BIC values, it explains that the resulting model is quite good.

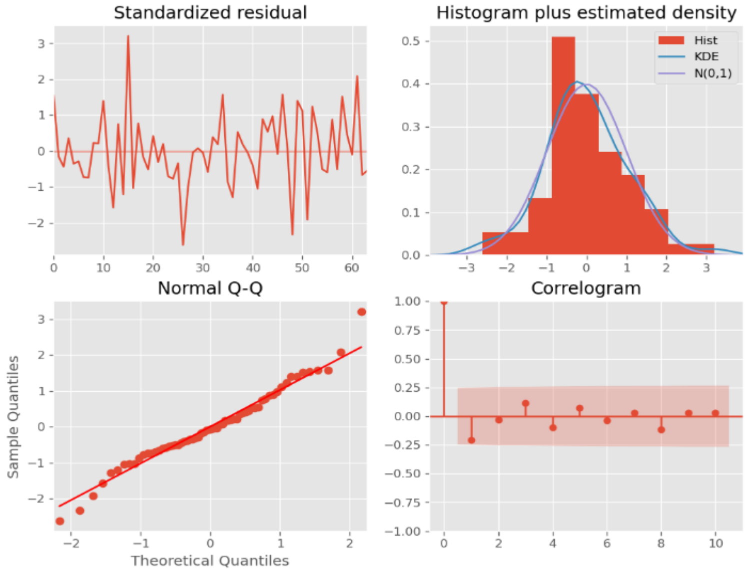

Fig. 1. Correlogram, Residual, Histogram, Normal Q Results

Next, we run Ljung-Box (Q) and Jarque-Bera (JB) tests to test the autonomy and normality assumptions of the model residuals. These two tests come up with the results Prob(Q) and Prob(JB) values greater than 0.05, which indicates that the assumptions of autonomy and normality of the residuals are acceptable. Next is the Heteroskedasticity test to test the presence of heteroscedasticity in the model residuals. The output result of the test is a Prob(H) value greater than 0.05, which means the hypothesis that the residual is homoscedastic is accepted. Based on testing the SARIMAX Model(1, 1, 0)x(0, 1, 1, 11) as a whole it can be concluded that the results of data analysis are meet the requirements.

Table 3 Sarimax Results

SARIMAX Results

Dep. Variable:	y	No. Observations:	65
Model:	SARIMAX(1, 1, 0)x(0, 1, [1], 11)	Log Likelihood	-1520.911
Date:	Mon, 24 Jul 2023	AIC	3047.823
Time:	10:19:56	BIC	3053.733
Sample:	01-01-2018	HQIC	3050.096
	- 05-01-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.4246	0.222	-1.916	0.055	-0.859	0.010
ma.S.L11	-0.6495	0.213	-3.052	0.002	-1.067	-0.232
sigma2	6.567e+23	1.98e-25	3.31e+48	0.000	6.57e+23	6.57e+23

Ljung-Box (L1) (Q):	0.51	Jarque-Bera (JB):	1.33
Prob(Q):	0.47	Prob(JB):	0.52
Heteroskedasticity (H):	0.78	Skew:	-0.27
Prob(H) (two-sided):	0.61	Kurtosis:	3.56

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Modeling

At the modeling stage, Jupyter tools were used with the Python programming language, in the data processing strategy that has been developed and the information that has been collected. From the picture you can see the number of sales at the Bank during January 2018 to May 2023, where the number of sales for the 5 years and 5 months is a significant upward trend, especially in 2021 to 2023. This data is the plotting data that will be predicted for the next 12 months.

The results of the Sales Volume predictions can be seen in the picture below, where there is a green line showing the prediction of an increase in the next 12 months from June 2023 to May 2024.

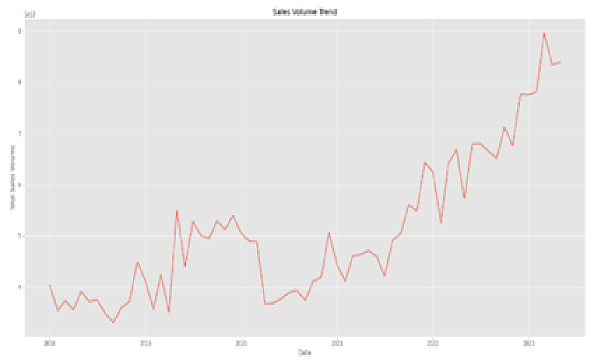

Fig. 2. Plot Sales Volume Data

Fig. 3. Results for the Next 12 Months

Evaluation

To evaluate the results of the ARIMA model in python, a test sample is used. While comparing the samples of predictions, the data is divided in time series for the last 12 months using data from January 2018 to May 2022. The picture below shows the evaluation results from the past 12 months, which are similar to the original model in the past 12 months. This is in line with what is expected from the results of the forecast evaluation.

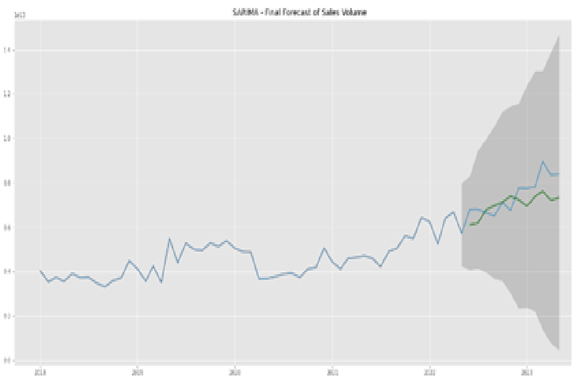

Fig. 4. Results for the Past 12 Months

The next evaluation is measuring a Mean Absolute Percentage Error (MAPE). From the picture, it can be depicted that the MAPE of forecasting for 12 years is 8%. This value is considered an excellent outcome for the forecasting process.

```
def forecast_accuracy(forecast, actual):
    mape = np.mean(np.abs(forecast - actual)/np.abs(actual))*100
    rmse = np.mean((forecast - actual)*2)*.5
    return({'mape': str(mape) + ' %', 'rmse':rmse})

forecast_accuracy(fitted_series, data_test)

{'mape': '8.45746793956651 %', 'rmse': -446640630914.57965}
```

DISCUSSION

Sales Volume Prediction for EDC Bank Merchants using the ARIMA Method

Based on data from January 2018 to May 2023, the results of analysis using the ARIMA method can predict sales volume at the Bank EDC Merchants from June 2023 to May 2024. This increase is believed to be caused by several factors. Recently, the Bank has begun to improve services to its merchants and customers. The Bank also provides a special reward program for Merchants who achieve large Sales Volumes. This approach encourages and motivates EDC Bank Merchants to continue to increase Sales Volume. Apart from that, many buyers are also interested in using debit or credit cards for purchase transactions, because there are special price promotions provided by banks that issue credit or debit cards. This figure is also in line with reports which state that in general transactions using EDC machines have increased quite significantly [33], [34].

Sales Volume Growth at the EDC Merchants Bank using the ARIMA Method.

The analysis results show monthly growth varies in percentage. During the 12 months of prediction, 2 months experienced a decline, namely in December 2023 and March 2024. In January, there was an increase of 2.38% because many buying and selling transactions occurred towards the end of the year and the beginning of the year, often triggered by special promotions. In February sales volume increased by 5.56% which can be attributed to the Chinese New Year celebrations, and the Bank is on SALE to celebrate the event. Over 12 months, the average sales volume growth reached 1.25%.

Business Perspective in Sales Growth Aspects

The results of this research reveal that forecasting using the ARIMA method technique indicates that sales at Merchant Bank will indicate significant sales growth. Based on the prediction results, there will be an increase in sales of 16.21% during the 12 month period starting from June 2023 to May 2024. In addition, a deeper analysis shows that sales growth has an average growth of 1.25%. Similar results, other studies using the ARIMA approach in the retail industry in supermarkets [35]and the manufacturing industry [36].

CONCLUSIONS AND RECOMMENDATIONS

Several conclusions can be drawn from the research results obtained. As the focus of the research is forecasting the sales volume of bank transactions using EDC machines, several conclusions related to both sales and the banking business itself, such as:

Insights into Sales Trends

Sales growth analysis provides a deeper understanding of sales trends, allowing companies to identify factors that influence sales fluctuations. This is very beneficial for company in making an appropriate marketing plans. This is align with other research results that indicate the correlation between forecasting and the importance of

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statistical data in banking industry [37], [38]. Whereas the latter research results are more focus on the bank performance itself instead of the outcome of the its performances which is achieving sales targets.

Guide to Business Strategy.

By knowing more accurate sales volume estimation, the Bank can design in more detail the operational business strategy, to maximize sales results. In conclusion, predictions of Sales Volume growth with EDC machines at Bank Merchants can help in developing strategy, particularly in commercial strategy and making business decisions in the future. This research illustrates the close relationship between promotional efforts, customer preferences, and market movements in influencing sales performance.

Importance of Special Promotions.

The research results show that the use of special promotions during holidays or at the end of the year can spur sales growth in a certain period. This highlights the importance of planning timely promotions to increase sales. Promotion in today's digital era often utilizes marketing channels through market places [4], [39]. Where with this approach consumer trust becomes an inseparable part of the success of a product's sales [40], [41].

Competitive Advantage.

In a very dynamic business environment, this is one measure of business competitiveness. Forecasting is an effective approach to describing market fluctuations and business competition. Hence, forecasting data and information become important information for companies in developing competitive strategies. The results of this study can also be combined with AI approaches to forecasting [42], or other widely used approaches [43].

In a business context, the ARIMA method in sales forecasting has flexibility, straightforwardness, and ease of contriving. This allows companies to take appropriate action to improve their sales performance. The results of this research underline the importance of sales data analysis in supporting strategic business decisions, by utilizing a statistical approach for Forecasting Techniques with ARIMA Time Series. From here, the company can acknowledge thoroughly the impact of special promotions or other sales strategies to optimize sales growth. This is an important step in increasing the company's competitive advantage.

For improvement, one of the recommendations for developing research results is the consideration of combining secondary and primary data. Primary data can be obtained through interviews with EDC merchants and analysis of consumer shopping interest trends. This will produce a more comprehensive dataset and may reveal previously unidentified factors that influence sales volume.

On the other hand, it is important to note that combining primary data in ARIMA analysis requires special attention to data validation, data cleaning, and potential bias in seller responses. This is to ensure the accuracy and completeness of primary data. Consequently, the cost of data collection and the need for analytical expertise may also need to be taken into consideration when using primary data.

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