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FORECASTING THE CLOSING PRICE OF META STOCKS USING A PULSE FUNCTION INTERVENTION ANALYSIS APPROACH

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Abstract: Meta Platforms, Inc. (META), the holding company that owns Facebook, Instagram, and WhatsApp, plays a crucial role in advancing artificial intelligence (AI). In early 2024, CEO Mark Zuckerberg announced an ambitious initiative to develop Artificial General Intelligence (AGI), leading to a significant rise in Meta's stock during the first quarter. Consequently, an analysis using the pulse function intervention method was conducted to model and forecast future data. The study utilized weekly data consisting of 124 training and 7 testing observations, spanning from March 13, 2022, to September 15, 2024. The optimal intervention model determined is ARIMA (0,2,1), with parameters b, s, r (0,0,1) and an intervention point at t = 99. Predictions for a further 8 periods resulted a MAPE of 9.682003% and an MSE of 2411.771. These findings suggest that investors should consider the influence of Zuckerberg's AGI strategy announcement on stock performance. The post-announcement surge indicates a favorable market reaction, and investors should closely follow the AGI project's development to assess META's long-term potential in the technology sector.

1. INTRODUCTION

Technological developments in recent years have drastically changed the way humans communicate, work, and acquire knowledge. Digital technologies such as the internet, cloud computing, and mobile devices have accelerated the globalization process and enabled instant access to information around the world. By the end of 2020, over 63% of the world's population was connected to the internet (International Telecommunication Union, 2021). In Indonesia, a survey undertaken by the Indonesian Internet Service Providers Association (APJII) indicated a notable increase in internet penetration, rising from 64% in January 2020 to 73.7% during the 2019-2020 period. Technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) enhance data processing capabilities, driving automation in sectors like manufacturing, agriculture, and healthcare (Tektelic Blog, 2023). A report from PwC (2018) forecasts that Artificial Intelligence (AI) will contribute $15.7 trillion to the global economy by 2030, underscoring its transformative potential across various sectors. Additionally, the generative AI market is projected to grow a lot, reaching $1.3 trillion by 2032, with a compound annual growth rate (CAGR) of 42%.

The development of artificial intelligence (AI) holds considerable promise for facilitating the attainment of the Sustainable Development Goals (SDGs). AI has great potential to revolutionize the health (SDG 3) and education (SDG 4) sectors. Through advanced medical data analysis and adaptive learning platforms, AI can unlock greater access to high-quality healthcare and relevant education (Sarnato et al., 2024). According to a PwC report (2018), AI can drive innovation in various sectors, thereby contributing to a 4% reduction in global carbon emissions by 2030, in line with climate action goals (SDG 13). According to a World Economic Forum (2020), indicates that AI could contribute to 9 of the 17 SDGs. It is essential to prioritize sustainability and ethics at every stage of AI development and application (Yu et al., 2018).

Meta Platforms, Inc (META), the holding company of Facebook, Instagram, and WhatsApp, plays a pivotal role in AI development, particularly through its extensive research and innovation the domains of machine learning, computer vision, and natural language processing (NLP). One of META's biggest contributions is in the development of open-source frameworks such as PyTorch, which is widely used by AI researchers and developers around the world (Paszke et al., 2019). META has also developed advanced AI models such as LLaMA (Large Language Model Meta AI), which is used for various NLP applications, including automatic translation and virtual assistants (Touvron et al., 2023). META has recorded significant growth in business innovation and diversification, especially in the areas of artificial intelligence and virtual reality, indicating strong growth potential for the company in the long term (Morningstar, 2024). In an effort to improve efficiency and productivity, Meta has allocated significant resources to AI research and development. For example, Mark Zuckerberg, Meta's CEO, announced in early 2024 the company's ambitious strategy of developing Artificial General Intelligence (AGI), which is considered a step up from the Generative AI that currently dominates the field of artificial intelligence. Meta has also developed multilingual and creative AI platforms, such as the “Imagine Me” feature that allows users to generate images based on descriptions, as well as the latest AI models such as Llama 3.1 that offer significant improvements in math calculations and reasoning.

Previous within the realm of artificial intelligence (AI) have demonstrated substantial advancements across various applications, particularly in the prediction and analysis of temporal data. These methods are widely used to model complex time patterns and make predictions based on historical data. Relevant research related to the topic raised including conducted by Alifia et al., (2024) which employed pulse function intervention analysis to predict global crude oil prices. This research identified the optimal intervention model as ARIMA (3,2,0) with an intervention order of $b = 0$, $r = 1$, $s = 2$, and MAPE of 2.8982%. Recent research on Meta Platforms company stock was also conducted by Lafifah and Murwanti (2024) with the title comparative analysis of financial performance before and after acquisition. This study employs a comparative approach with a paired sample t-test and the results show that there are significant differences in several financial ratios after restructuring. However, a number of analyses have shown that the challenges in predicting the value of Meta Platforms shares continue to evolve along with the dynamics of market changes, regulatory policies, and technological innovations. Therefore, current research that takes into account more innovative and adaptive market analysis approaches is important to maintain the relevance of knowledge in the effort to project and manage fluctuations in the value of Meta Platforms stock.

Based on the description above, this research aims to conduct an in-depth analysis of META stock movements using an intervention analysis approach. By adopting this method, it is expected to provide a new perspective in understanding the dynamics of META's stock price, especially in response to various interventional events and policies. Intervention analysis is considered an innovation in META stock studies, which allows researchers to more accurately identify the impact of specific events on stock price movements.

2. LITERATURE REVIEW

2.1. Time Series Analysis

Statistical techniques used to predict future trends in data by modeling current observations, understanding relationships between variables, and identifying process controls are referred to as time series analysis (Mills, 2019). This analysis includes two models, a deterministic model, where future time series states can be predicted with precision, and a probabilistic model, where future states are influenced by chance and only partially determined by past observations (Ryan et al., 2023). A common approach to time series data analysis that is known to be accurate in short-term predictions using current and past data, one of which is the Autoregressive Integrated Moving Average (ARIMA) method which consists of three fundamental elements, namely Autoregressive (AR), Moving Average (MA), and differencing (I) (Ojo & Olanrewaju, 2021). A non-seasonal ARIMA model is expressed as ARIMA (p, d, q), where p and q indicate the order of the AR and MA components, and d represents the differencing order. The ARIMA (p, d, q) model can be written mathematically as follows.

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B) a_t \tag{1}$$

with $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ and $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$.

Time series analysis demands the data to be stationary in mean and variance. To determine if the data is stationary in the mean, the Augmented Dickey-Fuller (ADF) Test can be conducted, expressed by the following regression equation.

$$\Delta_{\mathrm{yt}} = \alpha + \beta t + \gamma\, y_{t-1} + \delta_1 \Delta\, y_{t-1} + \delta_2 \Delta\, y_{t-2} + \cdots + \delta_{p-1} \Delta\, y_{t-(p-1)} + \varepsilon_t \tag{2}$$

Data stationarity can be assessed using ACF and PACF plots, which reveal gradual shifts in the mean. Thus, differencing is necessary after transformation (Purwa et al., 2020). According to Cryer and Chan (2008), the fundamental principle of Differencing entails subtracting the preceding observation Z_{t-1} based on present observations Z_t. In addition, differencing is also used to modify the ARIMA (p, d, q) model so that stationarity conditions are met.

Moreover, if the data exhibits non-stationarity in variance, it can be made stationary through the Tukey transformation. This transformation changes the value of Z_t to $Z_t^{(\lambda)}$ with the value of λ determining the type of transformation to be applied so that the data distribution is closer to normal. The Tukey transformation equation can be formulated as follows.

$$Z_t^{(\lambda)} = \begin{cases} Z_t^{\lambda}, & \lambda \neq 0 \\ \ln Z_t, & \lambda = 0 \end{cases} \tag{3}$$

After confirming the stationarity conditions for mean and variance, ACF and PACF plots can be used to identify the ARIMA order. The stages of ARIMA modeling consist of idenfication, parameter estimation, and diagnostic checking to ensure that the model satisfies the fundamental assumptions (Duchesne, 2020).

2.2. Intervention Analysis

According to Wei (2006), time series intervention analysis is a statistical approach for evaluating the effect of an intervention on time series variables. Interventions can involve intentional changes or unexpected events that affect the time series. The intervention model can be generally represented mathematically as follows.

$$Z_t = \frac{\omega_s(B)B^b}{\delta_r(B)} I_t^T + N_t \tag{4}$$

$$Z_t = \frac{\omega_s(B)B^b}{\delta_r(B)} I_t^T + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d}\,\alpha_t \tag{5}$$

where Z_t represents the intervention response variable at time t, I_t refers to the intervention variable, b denotes the starting point of the intervention effect, s indicates the duration of the intervention's impact on the data after time b, r refers to the intervention pattern established after time b and , $\omega_s = \omega_0 - \omega_1 B - \cdots - \omega_s B^s$, $\delta_r = 1 - \delta_q B - \cdots - \delta_r B^r$ and N_t signifies the optimal ARIMA model without the intervention effect.

The value of $b, r,$ and s in the intervention model are established by analyzing the cross-correlation plot that compares ARIMA model forecasts before the intervention with the actual post-intervention data. This order serves as a determinant for the transfer function. Generally, interventions are categorized into two types: step and pulse. If the intervention occurs over an extended period starting from time *T,* it is referred to as a step function, which can be mathematically illustrated as follows.

$$I_t^{(T)} = S_t^{(T)} = \begin{cases} 1, & t < T \\ 0, & t \geq T \end{cases} \tag{6}$$

In contrast, the pulse function represents an intervention event that occurs only once at time *T* and does not extend beyond that moment, which can be mathematically expressed as follows.

$$I_t^{(T)} = P_t^{(T)} = \begin{cases} 1, & t = T \\ 0, & t \neq T \end{cases} \tag{7}$$

2.3. Best Model Criteria

To The criteria for model accuracy and model selection used in this research include AIC and SBC (Murari, 2019), MSE (Ahmar, 2020), and MAPE (Badulescu, 2021) which are formulated as follows.

(1) Akaike's Information Criterion (AIC) $$\mathrm{AIC} = n\ln(\mathrm{MSE}) + 2p \tag{8}$$

(2) Schwarz's Bayesian Criterion (SBC) $$\mathrm{SBC} = n\ln(\mathrm{MSE}) + p\ln n \tag{9}$$

(3) Mean Square Error (MSE) $$\mathrm{MSE} = \frac{\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2}{n} \tag{10}$$

(4) Mean Absolute Percentage Error (MAPE) $$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\% \tag{11}$$

3. MATERIAL AND METHOD

3.1. Data

The dataset utilized in this research includes the weekly closing price of META stock from March 13, 2022 to September 15, 2024, taken from the investing.com website. The dataset is divided into 124 training points and 8 testing points. The significant spike on January 28, 2024 indicates that the intervention model likely follows a pulse function.

3.2. Data Analysis Procedure

The steps to model and predict with pulse function intervention are as follows.

Descriptive Analysis of META Stock Closing Price Data

(1) Describe the characteristics for META stock closing price data.
(2) Visualize the time series of all data to detect potential extremes that may suggest an intervention.
(3) Split the data into pre-intervention and post-intervention.

ARIMA Analysis of Pre-Intervention META Stock Closing Price Data

(1) Conduct data stationarity test in variance and mean on META stock price pre-intervention data.
(2) Apply a Box-Cox transformation if the variance of the pre-intervention data is non-stationarity for variance.
(3) If it does not meet the assumption of stationarity at the mean for the data before the intervention, differencing can be done.
(4) Determine the ARIMA model through examining the ACF and PACF plots of the pre-intervention data that have achieved stationarity.
(5) Use the OLS method for parameter estimation of the ARIMA model based on the pre-intervention data.
(6) Conduct diagnostic tests on the ARIMA model, encompassing tests for parameter significance, white noise in residuals, and residual normality, ensuring all assumptions are met.
(7) Select the optimal ARIMA model based on the lowest MSE value.
(8) Use the selected ARIMA model from pre-intervention data to predict post-intervention data.

Intervention Analysis on META Stock Closing Price Data Post Intervention

(1) Generate a CCF plot that compares the prediction data from before and after the intervention using the optimal ARIMA model.
(2) Determine the order (b, r, s) of the intervention model using the CCF plot.
(3) Perform parameter estimation of the intervention model using the OLS method.
(4) Evaluate the diagnostic performance of the intervention model, including parameter significance, white noise in residuals, and residual normality, ensuring all assumptions are fulfilled.
(5) Conduct model evaluation using information criteria such as the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) to identify the most suitable and parsimonious intervention model.
(6) Write down the best intervention model based on both diagnostic and information criteria results.
(7) Generate predictions based on the best model and evaluate forecasting accuracy using multiple performance measures such as MAPE and MSE.
(8) Compare actual and predicted data plots to visually assess model fit and predictive performance.

4. RESULTS AND DISCUSSION

4.1. Descriptive Analysis of META Stock Closing Price Data

To describe and know the overall META stock closing price data fluctuations from March 13, 2022 to September 15, 2024, a descriptive analysis can be carried out. The time series plot of the closing price of META stock is presented in Figure 1.

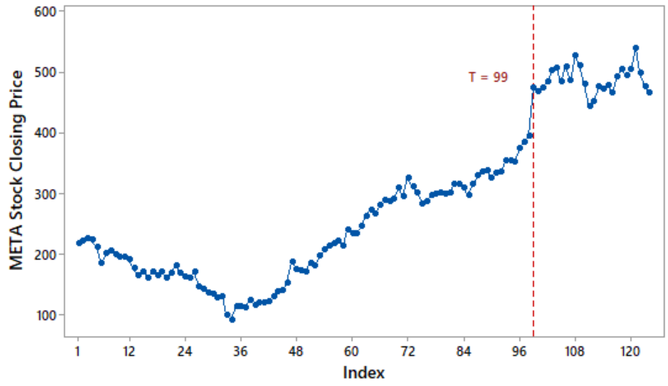
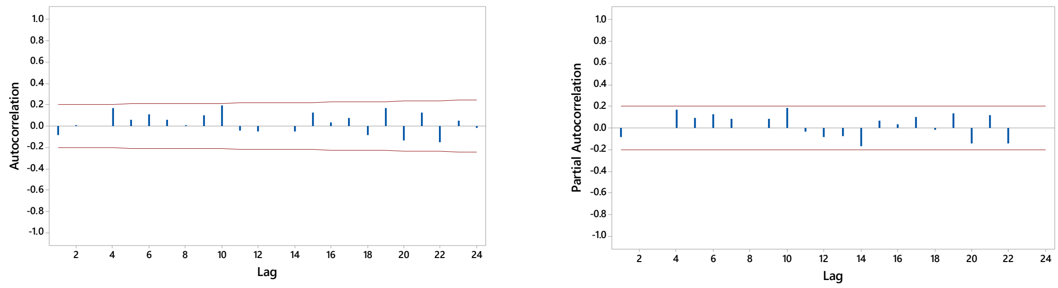


Figure 1. Time Series Plot of META Stock Closing Price Data

Figure 1 shows that the META stock closing price data plot tends to increase until the highest occurs at $t = 99$ on January 28, 2024 at a price of 479.99 USD, which is then set as the intervention point. The increase is due to the development of Artificial General Intelligence (AGI) which is considered more advanced. Thus, the distribution of pre-intervention data is obtained, from $t = 1$ (March 13, 2022) to $t = 98$ (January 21, 2024) and post-intervention $t = 100$ (January 28, 2024) to (July 21, 2024).

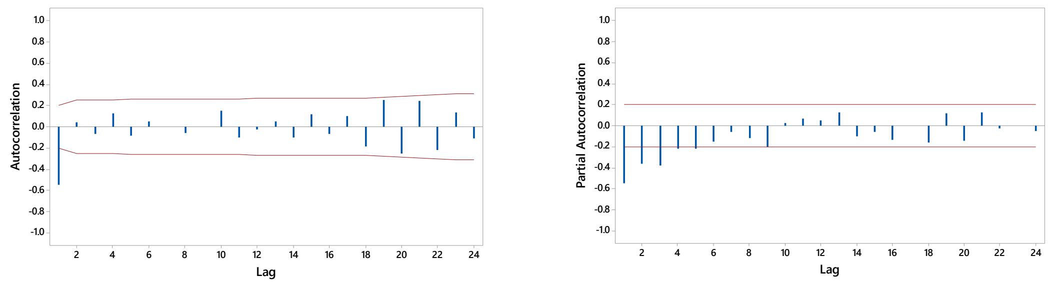
4.2. ARIMA Analysis of Pre-Intervention META Stock Closing Price Data

Initially, Figure 1 shows that the pre-intervention data is stationary but still has an upward trend with fluctuations. An ADF test yielded a p-value of 0.5741 (> 0.05), indicating non-stationarity in the mean. A Box-Cox transformation confirmed variance stationarity with a rounded value (λ) of 1.00 confirming the data is stationary in variance. Further differencing was applied to stabilize the mean, and the ACF and PACF plots from the first differencing ($d = 1$) is presented in Figure 2.



(a) (b)

Figure 2. ACF and PACF Plot Differencing 1



(a) (b)

Figure 3. ACF and PACF Plot Differencing 2

Figure 2 shows that there are no significant lags outside the boundary lines on the ACF and PACF plots, suggesting that the first-differenced series may already approximate a stationary or random walk process. Therefore, before applying the second differencing, it is important to verify whether the data indeed represent a random walk, as this could justify the use of an ARIMA(0,1,0) model and prevent overdifferencing. If non-stationarity persists, additional tests considering possible quadratic trends or seasonal patterns should be conducted prior to performing the second differencing. The ACF and PACF plots resulting from the second differencing ($d = 2$) is presented in Figure 3.

Figure 3 shows that the ACF plot has a spike at lag 1, while the PACF plot has spikes at lags 1, 2, and 3, confirming the data is stationary after two rounds of differencing. As a result, several candidate models are identified: ARIMA (1,2,0), ARIMA (2,2,0), ARIMA (3,2,0), ARIMA (0,2,1), ARIMA (1,2,1), ARIMA (2,2,1), and ARIMA (3,2,1).

Second, a parameter significance test will be conducted and a deterministic ARIMA (0,2,1) model is obtained with details presented in Table 1.

Table 1. Pre-Intervention ARIMA Model Results

Model	Parameter	Estimate	P-Value
ARIMA (0,2,1)	MA (1)	0,9951	0,000
Deterministic	Constant	0,1234	0,010

Table 1 shows that the ARIMA (0,2,1) model has a p-value (< 0.05) which means it has met the parameter significance requirements. In addition, the prerequisites of white noise and normal distribution are fulfilled on the residuals and obtained an MSE value of 133.409.

Third, after identifying the optimal model, specifically the deterministic ARIMA (0,2,1) for the pre-intervention data, the model can be writing according to Equation (1) as follows.

$$\phi_0(B)(1-B)^2 Z_t = \theta_1(B)a_t$$

$$(1-B)^2 Z_t = (1-\theta_1 B)a_t$$

$$Z_t - 2Z_{t-1} + Z_{t-2} = a_t - \theta_1 a_{t-1}$$

$$Z_t = 2Z_{t-1} - Z_{t-2} + a_t - \theta_1 a_{t-1}$$

Since it is deterministic, the value of c is added

$$Z_t = c + 2Z_{t-1} - Z_{t-2} + a_t - 0.9951a_{t-1}$$

$$Z_t = 0.1234 + 2Z_{t-1} - Z_{t-2} + a_t - 0.9951a_{t-1} \tag{12}$$

After establishing the deterministic ARIMA (0,2,1) model for the pre-intervention data, further analysis was conducted using the same model on the entire dataset to identify the suitable intervention analysis for this study. It was determined that the deterministic ARIMA (0,2,1) model applied to the overall data was not significant in the parameter significance test, preventing further continuation. Therefore, the intervention analysis method is deemed appropriate for this model.

4.3. Intervention Analysis on META Stock Close Price Data Post Intervention

The next step was to identify the intervention parameters for the optimal model derived from the data before the intervention, specifically the values of $b, r,$ and s, which were found to be $b = 0$, $s = 0$, and $r = 2$. Then, the parameter estimation test of the pulse function intervention model will be carried out and the estimation results are obtained with the parameters MA (1), ω_0, δ_1 is significant with p-value < 0.05 and parameter δ_2 is not significant because the p-value > 0.05. Therefore, further analysis will be carried out by reducing the insignificant order so that the orders used are $b = 0$, $s = 0$, and $r = 1$. The parameter estimation results of the pulse intervention model with this order are presented in Table 2.

Table 2. Intervention Model Significance Test Results

Model	Parameter	Estimate	P-Value
ARIMA (0,0,1) with $b = 0, s = 0, r = 1$	MA (1)	1.00000	< 0.0001
	ω_0	78.72703	< 0.0001
	δ_1	0.97273	< 0.0001

Table 2 shows that the intervention model with this order has qualified the significance of parameters because the p-value < 0.05. Additionally, the residuals of this model confirm to the prerequisites of white noise and normal distribution. The model also achieved the lowest AIC (997.2538) and SBC (1005.641) values among the candidate models, indicating its superior goodness of fit and parsimony. Combined with the fulfillment of white noise and normality assumptions, this model is therefore considered the most appropriate for predicting the closing price of META stock. Furthermore, the ARIMA (0,2,1) model with $b = 0,\ s = 0,\ r = 1$ can be written according to Equation (4) as follows.

$$Z_t = \frac{\omega_0(B)B^0}{\delta_1(B)} P_t^{(98)} + N_t$$

$$Z_t = \frac{\omega_0}{(1 - \delta_1 B)} P_t^{(98)} + 0.1234 + 2Z_{t-1} - Z_{t-2} + a_t \text{ RMSE } 951a_{t-1}$$

$$Z_t = \frac{78.7203}{(1 - 0.97273B)} P_t^{(98)} + 0.1234 + 2Z_{t-1} - Z_{t-2} + a_t - 0.9951a_{t-1} \quad (13)$$

Based on the results of the established model, forecasts will be generated for the upcoming 8 weeks. The prediction results are presented in Table 3.

Table 3. META Stock Closing Price Prediction Results

Date	Actual Data	Prediction Data	MAPE (%)
28/07/2024	488.14	467.6545	4.380477
04/08/2024	517.77	469.6383	10.248670
11/08/2024	527.42	471.6506	11.824300
18/08/2024	528.00	473.6907	11.465140
25/08/2024	521.31	475.7578	9.574662
01/09/2024	500.27	477.8511	4.691608
08/09/2024	524.62	47..9700	9.302665
15/09/2024	559.10	482.1137	15.968490
			9.682003

Table 3 shows that the prediction results have a MAPE value of 9.682003% and MSE of 2411.771, which means that the model's ability to predict is very accurate (Badulescu, 2021). Additionally, forecasts will be generated for 5 periods following the testing data presented in Table 4.

Table 4. META Stock Closing Price Prediction

Date	Prediction Results
22/09/2024	484.2816
29/09/2024	486.4731
06/10/2024	488.6873
13/10/2024	490.9239
20/10/2024	493.182

5. CONCLUSION

The increase in META's stock price due to the statement of Mark Zuckerberg, CEO of Meta regarding the company's ambitious strategy in developing Artificial General Intelligence (AGI) can be explained statistically through the analysis of pulse function intervention with modeling and prediction. The optimal intervention model selected is ARIMA (0,2,1) with parameters b, s, r $(0,0,1)$and intervention occuring at t = 99. Moreover, the predictions for the subsequent 8 periods resulted in a MAPE of 9.682003% and an MSE of 2411.771. These results that intervention analysis effectively assesses the impact of external events on significant shifts in the trend of time series data. The increase in share price following the announcement suggests that the market reacted positively to the potential innovations stemming from the AGI initiative. Therefore, it is crucial for investors to closely monitor the progress of the AGI project and future communications from the company, as these developments may influence META's long-term outlook in the technology sector.

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