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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

Performance of Deep Learning Models on Imputed Time Series Data: A Simulation Study and Application to Leading Airline Companies' Stock Price

İsmail YENİLMEZ [1], Kürşat ATMACA [2]

[1] *Eskişehir Technical University, Science Faculty, Department of Statistics, 26470, Eskişehir, Türkiye*

[2] *Turkish Revenue Administration, 06110, Ankara, Türkiye*

Abstract
In this study, the validity of imputation techniques for deep learning methods in time series analysis is investigated using datasets based on daily closing data in the stock market. Datasets of daily closing stock prices for Turkish Airlines, Deutsche Lufthansa AG, and Delta Airlines, as well as a simulated dataset, are used. LSTM, GRU, RNN, and Transformer models, which are deep learning models, are employed. The original dataset and datasets with 5%, 15% and 25% missing data are analyzed imputing linear, spline, Stineman, mean and random imputation techniques. The results show that model performance varies depending on the imputation technique and the rate of missing data. GRU and Transformer models are favored for their robustness and excellent performance. For handling missing data, using spline and Stineman imputations is advisable to maintain high model accuracy. This study emphasizes the usability of various imputation techniques and deep learning models in time series analysis. It assesses model performance using both MAPE and RMSE to gain a comprehensive understanding of predictive accuracy and reliability, aiming to guide future research by comparing these methods.
Keywords: Missing Data, Synthetic Data, Transformer Model, RNN, Simulation, Airline Stocks.

I. INTRODUCTION

Financial markets are characterized by their complex and dynamic nature. Time series analysis is a tool for identifying historical trends and patterns in financial data, aiding in the prediction of future movements. In financial markets, time series analysis and panel analysis are used for a variety of data types, including exchange rates, stock prices, etc. These analyses provide insights to make investment decisions, overcome risk management problems, and develop market strategies [1]. On the other hand, panel data analysis, which includes both cross-sectional and time dimensions, can also be applied [2].

Time series analysis employs a range of methods, from traditional statistical techniques, such as ARIMA, SARIMA, and Exponential Smoothing, to modern deep learning models (DLMs) like long short-term memory (LSTM), Gated recurrent unit (GRU), recurrent neural network (RNN), and Transformer model (TM). In particular, the widespread use of TM [3], which is a relatively new method, shows the speed of development in this field. On the other hand, the Box-Jenkins (BJ) method, which is traditionally used in time series analysis, and the Artificial Neural Networks (ANNs) method are compared for demand forecasting [4]. The time series data on Rwanda's and Brazil's GDP per capita are modeled using the conventional BJ approach and the innovative ANNs, respectively [5-6]. While ANNs and DLMs have advantages over traditional methods, it should not be overlooked that they also pose challenges such as hyperparameter tuning [7].

One of the significant challenges in time series analysis is the problem of missing data. Missing data can arise for various reasons and negatively impact analysis accuracy, reducing model prediction reliability and potentially leading to incorrect decisions. Various imputation techniques, such as linear, spline, Stineman, mean, and random imputation, have been used to estimate missing values and reconstruct the time series. The performance of these techniques varies with the nature and the proportion of missing values. The choice of imputation method is crucial to improve the accuracy and reliability of time series analysis [8-9].

In literature, the performance of three machine learning models (ARIMA, LSTM, GRU) is compared for time series forecasting using a Bitcoin price dataset, finding ARIMA to be superior to deep learning-based regression models [10]. The effectiveness of ARIMA and GRU models is assessed in predicting high-frequency stock prices,

Sorumlu Yazar: İSMAİL YENİLMEZ, **Tel:** 0222 335 05 80-7951, **E-posta:** ismailyenilmez@eskisehir.edu.tr
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demonstrating that the GRU model outperformed the ARIMA model in accuracy [11]. In a comprehensive literature review comparing ARIMA and machine learning algorithms for time series forecasting, as well as their integration in hybrid models, artificial intelligence algorithms exhibit superior predictive performance in most applications, hybrid statistical-artificial intelligence models outperform individual methods by leveraging the best features of both [12]. On the other hand, providing an overview of utilizing Transformer architecture in time series analysis, the study details core components such as self-attention mechanism, positional encoding, multi-head, and encoder/decoder, along with various enhancements and best practices for addressing time series tasks, showcasing the effectiveness of TM [13]. Systematically investigating the usage of TM in time series analysis, the study examines adaptations from both network structure and application perspectives, emphasizing empirical analyses, model size evaluations, and seasonal-trend decomposition to showcase TM's performance and potential for future research [14]. The importance of imputation techniques in handling missing data alongside time series analysis is a separate topic, and has been addressed in [15], investigating imputation of missing values in time series data using deep learning methods [15]. The effects of various imputation methods—including linear, spline, and Stineman interpolation, as well as mean and random sample imputation—on the goodness of fit of statistical models, using synthetic data to control for missing data rate and dataset size has been investigated [16].

The rest of this article is organised as follows. The second section of the study presents the methodologies employed. The third section shares the findings obtained from the analysis. The final section comprehensively assesses and discusses the results.

II. METHOD

2.1. Estimation Techniques

In this section, the modeling techniques and imputation methods utilized in the research are presented. Time series modeling techniques includes the traditional approach of ARIMA, while deep learning methods such as LSTM, GRU, RNN, and Transformer models are discussed. As for imputation techniques, commonly used methods in the literature are discussed, and presented, including Linear, Spline, Stineman, Mean, and Random imputation techniques.

The ARIMA model, characterized by the parameters *(p, d, q)*, integrates the autoregressive (AR) component of order *p*, differencing of order *d*, and moving average (MA) component of order *q*. Specifically, the AR component involves lagged values of the time series up to p periods, with coefficients denoted as α_i for $i = 1, 2, \dots, p$. The MA component incorporates q lagged forecast errors, with coefficients θ_j for $j = 1, 2, \dots, q$. The differencing parameter d indicates the number of times the time series is differenced to ensure stationarity. The ARIMA model is represented as in Equation (1):

$$\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right)(1 - L)^d X_t = \left(1 - \sum_{i=1}^{q} \theta_j L^j\right)\varepsilon_t \tag{1}$$

where X_t represents the time series value at time *t*, ε_t is the error term at time *t*, capturing any residual variation not explained by the ARIMA model, and L denotes backshift (lag) operator such that $L^k X_t = X_{t-k}$.

While traditional methods like ARIMA are still useful, especially for simpler, linear time series problems and for their interpretability, the flexibility, scalability, and performance of deep learning models make them increasingly preferable for more complex and large-scale time series forecasting tasks. Deep learning approaches like RNN, LSTM, and TM are gaining popularity because they can handle complex, non-linear relationships and long-term dependencies in time series data more effectively than traditional methods like ARIMA. Additionally, they require less manual feature engineering, scale well with large datasets, and can adapt more easily to changes in data patterns.

RNNs update their hidden state based on the input at the current time step and the hidden state from the previous time step. The hidden state update and output calculation are presented in Eq. 2, respectively.

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h)$$
$$y_t = \sigma_y(W_y h_t + b_y) \tag{2}$$

where h_t and x_t denote the hidden state and input at time step t, respectively, and h_{t-1} is the hidden state at the previous time step $t-1$. Here W_h, U_h, b_h and σ_h represent the weight matrix for the input x_t, the weight matrix for the hidden state h_{t-1}, the bias term, and the activation function for the input layer, respectively, while y_t, W_y, b_y, and σ_y denote the output at time step t, the weight matrix for the output, the bias term for the output, and the activation function for the output layer, respectively.

The LSTM model can capture long-term dependencies in sequential data and is presented through five equations: the forget gate, input gate, cell state update, output gate and hidden state update. Among these five steps, the forget gate step, presented in Eq.3, is often considered the most significant.

$$f_t = \sigma(W_f \, . [h_{t-1}, x_t] + b_f) \tag{3}$$

where f_t and x_t represent the forget gate activation vector at time step t and the current input, respectively; W_F and b_f denote the weight matrix and bias vector for the forget gate, respectively; σ is the sigmoid activation function; and $[h_{t-1}, x_t]$ denotes the concatenation of the previous hidden state h_{t-1}.

GRU networks simplify the LSTM architecture by combining the forget and input gates into a single update gate and merging the cell state and hidden state. The hidden state update equation is as presented in Eq.4.

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h_t} \quad \textbf{(4)}$$

where h_t, z_t, and $\widetilde{h_t}$ represent the hidden state, the update gate, and the candidate hidden state at time step t, respectively; h_{t-1} is the hidden state at time at the previous time step $t-1$, and $\odot$ denotes matrix multiplication.

The TM is a type of neural network architecture that utilizes self-attention mechanisms to capture dependencies between different time steps in the data [3]. The key equation in the Transformer model is the self-attention mechanism, which computes the weighted sum of values based on the similarities with keys. This mechanism is as presented in Eq.5:

$$output(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad \textbf{(5)}$$

Q, K, V represent the query, key, and value matrices, respectively. d_k denotes the dimensionality of the key vectors.

2.2. Imputation Techniques

Information about the commonly used imputation techniques used in the study is briefly presented below:

- *Linear Imputation*: This method fills missing values with a linear interpolation between adjacent known data points. It assumes a linear relationship between consecutive observations [8].
- *Spline Imputation*: Spline interpolation is a non-linear method that fits a series of polynomial functions between data points to create a smooth curve, providing a smooth estimation of missing values [17].
- *Stineman Imputation*: Stineman imputation could theoretically refer to using the Stineman interpolation method to estimate missing values in a dataset. The Stineman interpolation method aims to preserve the data's monotonicity and convexity/concavity [18].
- *Mean Imputation*: In mean imputation, missing values are replaced with the mean of the available data. It is a simple and commonly used method but may not capture the underlying patterns in the data [19].
- *Random Imputation*: This technique fills missing values with randomly selected values from the observed data. While it is easy to implement, random imputation may introduce noise into the dataset and distort the original distribution [8].

Each imputation method has its advantages and limitations, and the choice depends on the nature of the data and the specific objectives of the analysis.

III. FINDINGS

3.1. Simulation

A synthetic dataset of 4,500 units is produced for the years 2006-2024. The stock price is modeled with a linear trend, starting from 50 Turkish Liras and reaching 150 Turkish Liras. Normally distributed random variables are used to create random noise in price changes, with the dataset representing end-of-day data and daily fluctuations in stock prices. The seasonal component of prices is modeled with a sine function $[f(.) = sin(.)]$ repeated at certain intervals. To increase the realism of the simulation, outliers with high volatility are added to randomly selected time periods to represent the impact of unexpected market events or news.

For time series analysis, deep learning approaches such as RNN, LSTM, GRU, and Transformer models are used. Various data imputation techniques, including linear, spline, Stineman, mean, and random imputation methods, are employed. The models are tested with 0% (complete data), 5%, 15%, and 25% missing data. The uniform distribution is used to reduce the data [20]. The Python programming language is used for the analysis, and the results are presented in Table 1.

For non-imputation (0%), TM performs the best in terms of the mean absolute percentage error (MAPE) and R^2 but has a higher the root mean square error (RMSE) compared to RNN, LSTM, and GRU. Linear, spline, and Stineman imputations maintain high accuracy with moderate increases in errors as imputation rates increase. Mean and random imputations result in significant errors and a decrease in prediction accuracy. TM generally provides the best accuracy (lowest MAPE and highest R^2), making it the preferred choice when imputation rates are low to moderate. GRU and TM perform better with higher imputation rates compared to LSTM and RNN. Linear, spline, and Stineman imputations are preferred for maintaining model performance across all estimators. Mean and random imputations result in significant errors and should be avoided if possible.

3.2. Analysis of stock market data

End-of-day data for the stock prices of Turkish Airlines (THYAO), Lufthansa (LHA.DE), and Delta Airlines (DAL) are analyzed. These three airlines, which are among the top 10 leading airlines in the world, are included in the study. The same stages applied in the simulation are used in this analysis as well. Our goal is to compare the results from the synthetic data with those from real data applications [21]. The analysis of the stock prices of these three airline companies from 2006 to 2024 is presented in Tables 2-4 for THYAO, LHA.DE, and DAL, respectively.

For the THYAO dataset, TM and GRU exhibit the best performance with low MAPE and RMSE, and high R^2, indicating accurate and reliable predictions without missing data under non-imputation (0%). Linear and spline imputations are more effective, with spline being slightly better. Stineman imputation is also effective, but mean and random imputations lead to poor performance. GRU and TM are the most robust and accurate, especially with the appropriate imputation methods. GRU and Transformer models also show the best overall performance, particularly when using spline and Stineman imputations.

For the LHA.DE dataset, GRU exhibits the best performance with the lowest RMSE and relatively low MAPE, indicating accurate and reliable predictions without missing data. TM also shows strong performance under non-imputation (0%) since it produces smallest MAPE. Linear and spline imputations are more effective, with spline being slightly better. Stineman imputation is also effective, but mean and random imputations lead to poor performance. GRU and Transformer models show the best overall performance, particularly when using spline and Stineman imputations.

For the DAL dataset, the results are similar to those obtained for other datasets when imputation is employed. GRU and TM outperform the other methods considered in this study when combined with the spline and Stineman imputation techniques, particularly as the imputation rate increases.

IV. CONCLUSION

The comparison of traditional and deep learning methods on both original and imputed data has not been extensively explored in the literature as far as we know. This study investigates the imputation of missing data and evaluates the performance of deep learning techniques, utilizing datasets from Turkish Airlines, Lufthansa, Delta Airlines, and simulated synthetic data. The study employs RNN, LSTM, GRU, and TM. The datasets are imputed to include 5%, 15%, and 25% missing data, which are then imputed using Linear, Spline, Stineman, Mean, and Random imputation methods. The analysis of the four tables for datasets THYAO, LHA.DE, DAL, and Synthetic datasets across various imputation techniques provides a comprehensive overview of model performance under different conditions.

Performance without missing data (0% imputation): Across all datasets, TM consistently shows the lowest MAPE and RMSE, indicating superior accuracy and reliability. GRU and LSTM models also perform well, with RNN exhibiting slightly higher error rates. The high R^2 values for all models across datasets indicate that the models explain a significant proportion of the variance in the data without any missing values.

Impact of imputation techniques: Linear and Spline Imputations generally result in moderate increases in MAPE and RMSE across all models and datasets, with spline imputation showing slightly better performance than linear imputation. RNN models exhibit a more significant increase in errors compared to LSTM, GRU, and Transformer models. Stineman imputation maintains low and stable MAPE and RMSE values, particularly for GRU and Transformer models, indicating effective handling of missing data. Mean and random imputations led to significant increases in MAPE and RMSE across all models and datasets, with random imputation resulting in the most drastic deterioration in performance. This indicates that these methods are ineffective for handling missing data in time series forecasting.

While performing adequately without missing data, RNNs struggle significantly with higher rates of imputation, particularly with mean and random methods. LSTM models demonstrate robust performance, handling linear and spline imputations well but showing moderate increases in errors with higher rates of mean and random imputations. GRU models consistently show the best overall performance across all imputation techniques and datasets, maintaining low error rates and high R^2 values. TM models excel particularly with spline and Stineman imputations, maintaining very low MAPE and RMSE values. However, they also exhibit increased sensitivity to mean and random imputations, similar to other models.

The comprehensive analysis of the THYAO, LHA.DE, DAL, and Synthetic datasets under various imputation scenarios reveals several key conclusions.

For model performance: TM and GRU models consistently outperform RNN and LSTM models, particularly in the presence of missing data. This is evident from their lower MAPE and RMSE values across different imputation techniques.

For effective imputation techniques: Spline and Stineman imputations are more effective in maintaining model performance, while mean and random imputations lead to significant performance degradation. This underscores the importance of selecting the appropriate right imputation technique in time series forecasting.

For robustness to missing data: GRU and TM exhibit greater robustness to missing data, maintaining accuracy and low error rates across different imputation methods and missing data rates.

For metric correlation: The correlation between MAPE and RMSE suggests that both metrics should be considered for a comprehensive evaluation of model performance. Although they generally align, their different sensitivities to outliers provide complementary insights into model accuracy.

For practitioners in the field of time series forecasting, GRU and Transformer models are recommended due to their robustness and superior performance. When dealing with missing data, spline and Stineman imputations should be preferred to ensure minimal degradation in model accuracy. Avoid using mean and random imputations, as they significantly impair model performance. Finally, always evaluate model performance using both MAPE and RMSE to capture a complete picture of the model's predictive accuracy and reliability.

Future research can further expand on the findings of this study by examining additional deep learning architectures and prediction techniques to assess their effectiveness in handling missing data. Extending this to include not only time series prediction but also other types of data, such as health and environmental science datasets, would increase the generalizability of the results.

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DISCLAIMER: The data utilized in this study are publicly accessible real-world datasets. This research focused on evaluating the performance of various deep learning methods and imputation techniques using these datasets. The study does not provide any commentary or recommendations regarding the buying, selling, or other actions related to companies' stocks. Therefore, we bear no responsibility for such actions. As the data used are publicly available, no permissions were required for this study.

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APPENDICES

Table 1. Results for synthetic dataset

SYNTHETIC			**Lin. Imp.**			**Spl. Imp.**			**Sti. Imp.**			**Mea. Imp.**			**Ran. Imp.**		
		0%	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**
RNN	**MAPE**	0.90	1.24	1.27	1.60	1.12	1.16	1.84	1.01	1.10	1.63	4.24	5.09	13.62	5.83	11.92	28.67
	R^2	0.98	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99	0.81	0.77	0.26	0.70	0.32	0.24
	RMSE	0.57	1.61	1.73	2.02	1.45	1.51	2.40	1.31	1.45	2.09	9.24	10.19	19.95	12.40	22.43	33.92
LSTM	**MAPE**	0.85	1.79	1.83	1.91	1.60	1.64	1.66	1.42	1.52	1.81	4.65	3.59	10.13	4.29	10.15	12.12
	R^2	0.98	0.99	0.99	0.98	0.98	0.98	0.98	0.99	0.99	0.98	0.82	0.83	0.40	0.73	0.35	0.22
	RMSE	0.53	2.30	2.33	2.42	2.10	2.12	2.13	1.91	1.97	2.32	8.91	8.71	17.99	11.65	21.95	26.72
GRU	**MAPE**	0.86	0.91	0.94	0.99	0.90	0.91	1.10	0.88	0.90	0.96	3.74	3.55	13.12	4.31	11.08	14.91
	R^2	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.82	0.83	0.39	0.73	0.33	0.23
	RMSE	0.53	1.19	1.24	1.31	1.15	1.18	1.45	1.15	1.17	1.23	8.82	8.73	18.11	11.71	22.21	26.53
TM	**MAPE**	0.15	0.17	0.21	0.27	0.19	0.20	0.22	0.18	0.19	0.21	8.90	3.13	10.66	4.10	10.90	16.10
	R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.50	0.60	0.45	0.41	0.38	0.22
	RMSE	1.76	1.96	2.13	2.50	1.96	2.01	2.48	1.98	2.07	2.13	6.10	2.60	6.90	3.60	8.60	10.14

Table 2. Results for Turkish Airlines stocks' dataset

THYAO			**Lin. Imp.**			**Spl. Imp.**			**Sti. Imp.**			**Mea. Imp.**			**Ran. Imp.**		
		0%	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**
RNN	**MAPE**	2.71	7.18	8.24	10.09	6.11	7.85	9.52	6.35	7.86	12.55	24.30	52.82	34.52	46.83	96.7	176.24
	R^2	0.99	0.94	0.90	0.87	0.95	0.95	0.92	0.94	0.93	0.81	0.51	0.28	0.16	0.43	0.31	0.11
	RMSE	3.64	17.41	21.38	25.74	14.04	15.48	17.91	17.01	17.72	31.37	48.96	57.53	59.13	89.17	87.53	84.14
LSTM	**MAPE**	3.24	4.10	4.40	4.44	2.86	3.41	3.95	2.92	3.47	4.60	24.61	33.54	42.84	49.74	81.76	122.00
	R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.69	0.70	0.51	0.35	0.26	0.22
	RMSE	3.77	4.74	6.09	6.78	3.35	3.98	4.02	5.18	6.23	5.80	38.60	36.79	45.17	85.57	86.04	88.21
GRU	**MAPE**	2.05	2.52	2.75	2.94	2.45	2.55	2.72	2.65	2.82	2.98	24.42	39.76	48.62	36.46	79.11	130.58
	R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.89	0.72	0.66	0.10	0.24	0.21
	RMSE	2.71	3.12	3.19	3.36	3.08	3.60	3.82	4.35	4.62	4.78	23.21	35.60	37.57	75.27	85.09	87.71
TM	**MAPE**	0.41	0.68	1.08	1.43	0.46	0.47	0.54	0.44	0.50	0.58	25.47	49.42	57.53	94.03	122.60	179.70
	R^2	0.99	0.99	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.86	0.66	0.45	0.51	0.22	0.22
	RMSE	2.25	2.43	2.58	4.38	2.41	2.47	3.34	2.45	2.58	3.88	28.76	43.65	54.36	55.59	84.75	85.42

Table 3. Results for Deutsche Lufthansa AG stocks' dataset

LHA.DE			**Lin. Imp.**			**Spl. Imp.**			**Sti. Imp.**			**Mea. Imp.**			**Ran. Imp.**		
		0%	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**
RNN	**MAPE**	1.91	1.93	2.03	2.99	1.93	2.01	2.08	1.9	2.03	2.04	6.12	8.18	19.95	18.38	16.02	26.04
	R^2	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.91	0.78	0.53	0.59	0.43	0.25
	RMSE	0.21	0.22	0.23	0.31	0.22	0.23	0.24	0.21	0.22	0.22	0.82	1.25	1.77	2.01	2.64	3.47
LSTM	**MAPE**	1.72	2.03	1.94	4.18	1.85	1.90	2.03	1.88	1.90	1.94	6.20	9.52	12.38	9.31	15.23	25.07
	R^2	0.99	0.99	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.91	0.80	0.69	0.69	0.45	0.25
	RMSE	0.20	0.23	0.22	0.46	0.21	0.21	0.23	0.21	0.21	0.22	0.82	1.20	1.44	1.76	2.60	3.46
GRU	**MAPE**	1.65	1.88	1.89	2.38	1.80	1.78	1.86	1.78	1.86	1.87	5.57	9.84	11.95	9.49	12.96	22.28
	R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.91	0.80	0.68	0.69	0.45	0.29
	RMSE	0.19	0.20	0.21	0.27	0.20	0.21	0.22	0.21	0.21	0.21	0.83	1.20	1.46	1.75	2.59	3.38
TM	**MAPE**	0.38	0.39	0.44	0.51	0.39	0.40	0.45	0.48	0.45	0.50	9.30	8.71	10.88	7.00	10.85	17.97
	R^2	0.99	0.99	0.99	0.91	0.99	0.99	0.97	0.97	0.96	0.97	0.42	0.53	0.34	0.47	0.23	0.22
	RMSE	0.34	0.35	0.43	0.72	0.35	0.39	0.62	0.53	0.47	0.53	0.92	0.83	0.99	0.99	1.51	85.43

Table 4. Results for Delta Airlines stocks' dataset

DAL			**Lin. Imp.**			**Spl. Imp.**			**Sti. Imp.**			**Mea. Imp.**			**Ran. Imp.**		
		0%	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**	**5%**	**15%**	**25%**
RNN	**MAPE**	1.86	2.07	2.65	2.94	2.01	2.08	2.63	2.05	2.10	2.60	8.66	13.23	16.21	13.13	22.88	36.33
	R^2	0.99	0.98	0.97	0.97	0.99	0.99	0.96	0.99	0.98	0.97	0.78	0.54	0.36	0.68	0.38	0.22
	RMSE	1.01	1.10	1.43	1.49	1.07	1.10	1.76	1.09	1.13	1.35	4.59	6.55	7.52	5.94	9.01	11.11
LSTM	**MAPE**	1.82	2.01	2.27	4.16	1.95	2.01	2.93	1.98	2.03	3.87	7.06	11.15	13.38	13.64	25.88	35.13
	R^2	0.99	0.98	0.98	0.95	0.99	0.99	0.94	0.99	0.98	0.95	0.81	0.59	0.48	0.67	0.35	0.21
	RMSE	0.99	1.09	1.18	2.19	1.06	1.09	1.95	1.07	1.09	2.03	4.23	6.13	6.79	5.99	9.29	11.10
GRU	**MAPE**	1.78	1.96	2.16	2.24	1.92	2.00	2.73	1.95	1.98	2.36	6.41	13.41	17.68	14.31	23.59	35.20
	R^2	0.99	0.99	0.99	0.98	0.99	0.99	0.97	0.99	0.99	0.99	0.92	0.77	0.66	0.82	0.61	0.46
	RMSE	0.99	1.09	1.14	1.17	1.05	1.07	1.49	1.06	1.08	0.62	2.24	3.38	3.96	3.28	4.91	5.96
TM	**MAPE**	0.37	0.44	0.47	0.48	0.39	0.4	0.44	0.41	0.44	0.46	7.83	13.59	18.32	9.06	20.49	29.94
	R^2	0.99	0.98	0.98	0.97	0.99	0.98	0.97	0.97	0.97	0.97	0.92	0.79	0.67	0.89	0.71	0.50
	RMSE	0.98	1.28	1.44	1.47	1.16	1.21	1.41	1.24	1.27	1.44	2.30	3.67	4.34	2.76	4.52	5.75