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Article

Adaptive Multi-Scale Trend–Temporal Multiplicative Attention for LSTM-Based Time Series Forecasting

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Abstract: The problem of accurately forecasting complex and long time series with the presence of long-range dependencies, changes in trends, and dynamically evolving temporal characteristics persists. Even though LSTM networks are able to model sequence dependencies effectively, temporal characteristics may not be properly captured when the sequence contains complex and dynamically evolving patterns. While conventional attention models are able to tackle this problem by providing differently weighted hidden state representations, their attention computation mechanism mainly depends on the similarity of hidden states and ignores temporal recency, multi-scale trend information, and changing local temporal regimes. In order to overcome this problem, we propose a new Adaptive Multi-Scale Trend and Temporal Multiplicative Attention LSTM (AMSTTMA-LSTM) approach for time series forecasting. The approach is able to dynamically define the importance of historical observations taking into account the semantic similarity, temporal recency, multi-scale trend information, and changing temporal regimes. Firstly, the time series sequence is processed through several LSTM layers in order to get the hidden-state representations encoding temporal dependencies. Then, the adaptive temporal part is added to take into account the temporal relevance of observations according to the temporal distance from the forecasting point. Multi-scale differences are applied to extract the information about the local trends at different time intervals. First and second-order temporal variations are taken into account to encode the information about local changes in the temporal behaviour. These features are encoded in complementary feature representations that are then combined in the adaptive factor gating module in order to dynamically learn the contribution of similarity, temporal recency, and multi-scale trend information in each time point. These factors are combined through the multiplicative attention formulation to get dynamic attention scores, which are then normalized to get attention weights. Finally, the attention-weighted hidden states are combined into the dynamic context representation used for the time series forecasting task.
Keywords: LSTM, Adaptive Attention, Multiplicative Attention, Multi-Scale Trend, Temporal Recency, Temporal Regime, Time Series Forecasting, Deep Learning

1. INTRODUCTION

Forecasting plays an important role in many industries as the ability to forecast future trends and behaviour helps to make the decisions and plan strategically. Traditionally, one of the most common approaches to making forecasts is the use of the ARIMA model, as it is simple and quite efficient for linear data. Nevertheless, there are several limitations of ARIMA that are revealed when working with non-linear data, missing data sets, and long-term sequence forecasting [1]. In order to address the problem, new methods need to be used.

Recent developments in machine learning, such as the development of the LSTM network, have opened up some perspectives in terms of overcoming these restrictions. The LSTM neural network is just one type of Recurrent Neural Network (RNN). It is well adapted to work with sequential and time series data and can handle long-term dependencies [2].Nevertheless, there are several problems with classic LSTM concerning long-range dependencies and memory bottlenecks as LSTM treats all time steps equally [3].

For the improvement of the performance and interpretation of the LSTM models, the introduction of the Attention mechanism has been suggested. With the help of the attention mechanism, the model can highlight significant time steps, thus becoming more flexible regarding the processing of complex data and longer time series, which are useful for financial forecasting and natural language processing tasks [4]. The Attention-LSTM model not only covers the disadvantages of the convolutional approach it also gives better accuracy and flexibility of the forecasting [5].

Speaking of the application of machine learning and artificial intelligence in agriculture, it should be mentioned that the integration of both of these technologies led to the appearance of AI-powered smart farming portals. The algorithm allows giving accurate recommendations about crop choice, yield forecast, and soil fertility, thus increasing the efficiency of farming and making it more sustainable [6]. The introduction of the Google Translate API ensures the use of the portal by people with different native languages [7].

There is also good potential for global scalability and adaptation of this technology to varied conditions of farming as these portals can be adapted to different agricultural zones and practices. Using local soil and climatic data, these portals give personalized recommendations depending on specific conditions [8]. The use of cloud infrastructure and IoT devices makes it possible to improve the functioning of this system even more [9].

2. RELATED WORKS

In the sphere of time series forecasting the significant progress has achieved due to implementation of machine learning models and addressing the issues associated with conventional models like ARIMA. There is a growing interest shown in novel neural network models like LSTMs and their further enhancement with Attention to boost performance. In this section, literature relevant to the approach mentioned above is discussed along with the applications, advantages, and disadvantages of this method in different industries, from agriculture to finance and energy.

The literature related to time series forecasting shows that changing from traditional models to more complex machine learning models. Even though ARIMA is quite effective when it comes to linear time series forecasting, it still faces certain challenges in dealing with non-linear patterns and long-term forecasting data. To solve these issues, LSTMs are implemented due to their capability to detect complicated connections in the dataset.

The suggestion to incorporate Attention into LSTM models is presented as one of the ways to solve the problems faced with the application of LSTMs due to the possibility to emphasize the importance of specific time moments. In the field of agriculture, AI solutions has been developed for building smart farming. In this way, machine learning algorithms help to suggest specific actions that will allow increasing the productivity of crop farming and making it more sustainable [10]. The use of Google Translate API on these platforms provides the opportunity to access the information in spite of language barriers.

Bouktif et al. [11] The application of RNN and LSTM models for hydrological time series predictions shows the difference in performance, which means the need to choose the right model for each specific situation. The results once again prove that domain knowledge is crucial in obtaining quality predictions in environmental modeling. The attention mechanism helps to improve generalization.

D. Tian et al. [12] Hybrid MA-ARIMA-GASVR model performs better than the traditional models when it comes to forecasting temperatures in a controlled agricultural environment. This model helps to solve the problems associated with ARIMA due to increased flexibility provided by the machine learning elements. Attention-LSTM can deal with missing values and long-term dependencies better than other models.

T. Fang & R. Lahdelma et al. [13] demonstrated the efficiency of SARIMA models in heat demand forecasting in district heating systems. My research proves the necessity to further develop the model in order to take into account changes in the environment. Attention-based models can be useful in capturing seasonal trends more accurately. Rohaifa Khaldi et al. [14] Proper selection of RNN cell structures is crucial in accurate time series behaviour prediction. The research highlights the importance of RNN customization depending on the dataset features. Attention-LSTM can dynamically change importance weights.

Md. Rasel Sarkar et al. [15] Ensemble learning algorithms, such as GATE, can increase the efficiency of time series forecasting through combining several predictive models. This approach prevents the limitations of a single model approach and shows improved adaptability to different datasets. Attention-LSTM can ensure the same level of efficiency and predictive power.

3. VARIOUS METHODS IN TIME SERIES FORECASTING

3.1. Convolutional Statistical Models

ARIMA (Autoregressive Integrated Moving Average): ARIMA method is one of the most popular and reliable methods for time series forecasting [16]. The dependencies in time series data, are described using an ARIMA model that contains components for moving averages (MA), differencing (I), and autoregression (AR).

The Use of ARIMA Model: Our forecasting methodology is based on the ARIMA model. With the help of this model, we can understand time series data as it takes into consideration autoregressive and moving average components and allows us to consider seasonality as well.

SARIMA (Seasonal ARIMA): SARIMA is just inherited from ARIMA and the non-seasonal autoregressive-moving average (ARMA) model that have already been mentioned. SARIMA models are denoted by the following notation: ARIMA(p, d, q)(P, D, Q)m, where (p, d, q) and (P, D, Q) m are the seasonal and non-seasonal parts of the model respectively. m is the number of seasons [17].

3.2. Deep Learning Models

LSTM (Long Short-Term Memory): RNN (Recurrent Neural Network) is an often-used deep learning network structure. In many cases, the problems with vanishing gradients and even exploding gradients make the training of RNNs especially hard due to long-term dependencies. The vanishing gradient problem can be solved by means of LSTM networks. The main element of the LSTM architecture is the LSTM unit which consists of several gates and cells and gives the final output.

GRU (Gated Recurrent Unit): GRUs have good performance in the field of sequence learning. Despite being used primarily for the forecasting of financial time series, their application in other areas is rather narrow. GRUs help solve vanishing and exploding gradients in the context of novel recurrent neural networks (RNNs).

3.3. Hybrid Models

Hybrid of ARIMA and LSTM: This ensemble method includes the use of both LSTM and ARIMA models according to the strengths of each of them by applying LSTM on nonlinear elements and ARIMA on linear elements of the data. Compared to all models reviewed, the hybrid of LSTM and ARIMA models had the lowest values for metric errors. The hybrid model outperformed others in terms of MAPE and RMSE. To enhance the performance of predictions, the hybrid model combining both LSTM and ARIMA was created. Time series data consist of nonlinear and linear elements, hence the autopilot data should as well.

3.4. Ensemble Learning Techniques

Guided Approach for Time Series Ensemble Forecasting (GATE): A new framework of ensemble learning called GATE has been proposed that can help to improve accuracy and robustness in time series forecasting, which is an essential feature of engineering practices in the current era. Due to the variable nature of the time series, it is difficult for DL algorithms to give accurate forecasts, even though their ability to forecast time series data has been proven. To solve this issue, the GATE framework utilizes the technique of unsupervised learning to guide the output of the ensemble through a guided network using RNN, LSTMs, and Conv-LSTM.

4. PROPOSED METHOD

The conventional LSTM architecture works effectively in learning temporal dependencies from sequential data. Nevertheless, when the length of the input sequence is large, the model will not be able to preserve all the information required for the forecast. Despite the improvement brought by attention mechanisms in the LSTM model through assigning weights of varying importance to hidden states, conventional attention focuses only on the degree of similarity between the current state and past hidden states. Consequently, the temporal distance of an observation and its changing pattern might not be adequately captured in the process of attention calculation. In time series forecasting, however, recent observations and local changes can provide additional information for future predictions. In order to improve the conventional LSTM model by overcoming the aforementioned limitations, we propose the Adaptive Multi-Scale Trend-Temporal Multiplicative Attention LSTM (AMSTTMA-LSTM) architecture. proposed attention mechanism considers the relevance, temporal recency, and changing trend of observations in addition to their similarity to the current hidden state. Moreover, contrary to conventional models, which use fixed importance of each component, our attention mechanism is able to learn the importance dynamically depending on the current temporal characteristics of the input sequence. At first, the input sequence is provided to LSTM layers, stacked one upon another, which produce a sequence of hidden states. A conventional LSTM encoder is used to capture temporal dependencies in the input sequence and generate hidden states representing different time steps. Assuming that the input sequence is denoted as $X=\{x1,x2,\ldots,xT\}$, where(T) is the sequence length. The sequence of hidden states obtained from the LSTM encoder is denoted as $H=\{h1,h2,\ldots,hT\}$. The hidden state at the last time step (hT) will be considered as the current forecasting context and used in determining the relevance of past observations.

5. CASE STUDIES

Combining LSTM networks with an attention mechanism has proven to be extremely promising for many practical purposes, increasing the performance of time series prediction. Below are some examples of successful implementation of the LSTM-Attention model in practice.

5.1 Financial market forecasting

Precise prediction of trends in the financial market is important to achieve the best results. The LSTM-Attention model has been successfully applied in predicting stock market volatility and trends. Prioritization of time steps in this way makes the model pay more attention to the most important points and makes predictions more accurate. Such approach becomes highly valuable when dealing with dependencies in non-linear patterns.

5.2 Energy load forecasting

Models based on LSTM-Attention have also been applied in energy industry to forecast electrical load demands. Models predict energy consumption patterns and help adjust energy supply according to them. Adaptation to the changes in the environment through prioritizing relevant features becomes possible thanks to the attention mechanism.

5.3 Smart farming and agriculture

Smart farming technologies can use LSTM-Attention models to predict yields and optimize the use of resources in agriculture. Taking into account local climate and soil data, models offer customized solutions to farmers, which helps them make appropriate decisions and achieve better outcomes. Attention mechanisms allow focusing on the most important aspects of the environment.

5.4 Health care and public health

The healthcare industry can also benefit from LSTM-Attention models when predicting disease outbreaks and managing public health data. For example, during the COVID-19 pandemic, such models were used to forecast infection rates and the need for a certain amount of healthcare resources. Priority setting of time steps became extremely helpful in this situation.

5.5 Natural language processing (NLP)

Models based on LSTM-Attention become highly effective tools for improving NLP. Using this approach, one can achieve better results in tasks of language translation and sentiment analysis, because the attention mechanism allows to pay attention to the most important words in the text.

Integration of LSTM network architecture with the Attention mechanism has proven to hold much promise in terms of increasing the forecast accuracy as well as providing a more interpretable model. However, there are several barriers and constraints related to this method as shown below.

6. Challenges, Limitations, Comparative analysis

a. Challenges and limitations

Computational Complexity

Adding an attention mechanism to an LSTM model adds up to the computational complexity of the system due to the addition of attention weight calculation at every time step that could prove to be quite demanding especially for large sets of data and models with many parameters. Efficient training strategies will help to overcome these issues.

Memory and Resource Usage

Attention-LSTM models usually require many resources and memory. The need to store and calculate attention weights at each time step leads to increased memory usage which might be problematic especially for applications that do not have sufficient amount of resources.

Model Interpretability

While the introduction of the Attention mechanism helps to interpret the model better and find out the most important time steps, it makes the interpretation of how the attention weights were calculated more complicated.

Tuning Hyperparameters

The effectiveness of the Attention-LSTM model relies greatly on the choice of the appropriate set of hyperparameters like attention head number and attention layer size which calls for extensive experiments and tuning. This process requires great expertise in model optimization.

Risk of Overfitting

Due to the flexibility of the Attention-LSTM model it may be prone to the problem of overfitting especially when working with small datasets. In this case the model will start to learn the noise as if it were a pattern.

Scalability

Scaling the Attention-LSTM models to handle very large datasets or real-time applications can be challenging because of computational requirements and need for real-time processing.

Customization for Specific Domains

The effectiveness of Attention-LSTM models can greatly vary depending on the domain and type of the time series. It might be necessary to customize and adapt the model to work with specific properties of the data which can be complicated and resource-intensive.

6.1 Comparative Analysis: LSTM-Attention Model vs. Traditional and Hybrid Models

In the field of time series forecasting, the LSTM-Attention approach has proved to be a very useful technique, providing significant improvements over the traditional models like ARIMA and SARIMA as well as hybrid models. This section contains the comparison of these models in terms of performance and accuracy.

6.2 ARIMA and SARIMA Models

Performance and Accuracy

ARIMA (Autoregressive Integrated Moving Average): Very effective and simple-to-use method for linear data forecasting used for economic and agricultural forecasting (Kumar & Anand, 2014). But the model does not perform well in cases of nonlinearities and datasets with missing values.

SARIMA (Seasonal ARIMA): Extension of ARIMA that takes into account the presence of seasonality in the data (Fang & Lahdelma, 2016). However, it cannot handle long-term forecasts and is not flexible enough to adapt to changes in the environment.

The linear nature of both models limits their capability to capture complex nonlinear patterns and relationships. Extensive data pre-processing and inability to work with datasets with missing values and high volatility make these models inconvenient.

6.3 Hybrid Models

Performance and Accuracy

ARIMA-XGBoost Hybrid: This model combines the abilities of ARIMA to handle linear trends and the ability of XGBoost to work with non-linearities in order to increase the forecasting accuracy of the volatile markets [20].

ARIMA-LSTM Hybrid: Combining the abilities of ARIMA and LSTM models makes it possible to increase the forecasting accuracy in cases of forecasting of COVID-19 data [21].

Hybrid models usually involve increased computational complexity and tuning of multiple components. Increased training time and computational load are some disadvantages of hybrid models, especially when dealing with large datasets.

6.4 LSTM-Attention Model

Performance and Accuracy

LSTM (Long Short-Term Memory): LSTM networks are good in discovering long-term relationships in sequential data usually outperforming traditional models in cases of complex temporal patterns.

Attention Mechanism: The use of an attention mechanism allows the model to pay more attention to important time steps thus improving its interpretability and performance by focusing on important data points. The LSTM-Attention model dynamically assigns importance weights thus being adaptive to many types of datasets and domains.

The model is able to capture both linear and non-linear patterns being universal and applicable in a variety of areas including finance forecasting and smart farming. Thanks to a focus on important features the risk of overfitting is significantly reduced.

Increased computational complexity and memory requirements are some limitations of the model. Tuning of hyperparameters is also crucial for the performance of the model.

7. Experimental results and analysis

In order to assess the efficiency of the LSTM with Attention Mechanism in forecasting non-linear time series, a comparison analysis between the model and two benchmark approaches was performed. Specifically, the analysis involves comparison between the classic ARIMA model and the basic LSTM approach[22].

7.1 Dataset and pre-processing

In order to maintain the consistency of the experiment, all models were applied to the same artificial non-linear time series dataset constructed with the use of the sinusoidal function and Gaussian noise. These models have trouble capturing the non-linearity and temporal dependencies of the dataset. For the training and validation process, an 80:20 split was used, and all the datasets were scaled to the [0,1] interval before the models were trained.

As shown in Table 1, the classic ARIMA model has the worst performance of all compared models due to its linear nature and inability to reflect the long-term temporal dependencies. Even though the ARIMA model allows representing seasonality and trends to some extent, it cannot reflect the non-linear relationships present in the dataset.

At the same time, the LSTM approach has a better performance compared to the ARIMA model in all metrics. This is because the structure of LSTM is suitable for sequential information with long-term dependencies [23] which are common for non-linear time series.

Specifically, the LSTM with Attention Mechanism has the best performance compared to all the other models. The attention mechanism improves the capability of the LSTM to select important time steps in the sequence. As a result, it allows reducing the negative impact of irrelevant time steps and increasing the performance of the model.

Table 1: Comparative evaluation of ARIMA, SARIMA, LSTM, and LSTM-Attention Mechanism

Model	**MSE**	**RMSE**	**MAE**	**MAPE (%)**	**SMAPE (%)**	**R^2**
ARIMA	155.00	12.45	10.23	19.84	18.65	0.72
SARIMA	117.07	10.82	8.71	16.72	15.94	0.79
LSTM	53.29	7.30	5.90	12.36	11.48	0.88
LSTM - Attention Mechanism	**33.06**	**5.75**	**4.62**	**9.21**	**8.93**	**0.94**

The above table presents the comparative evaluation of ARIMA, SARIMA, LSTM, and LSTM with Attention Mechanism based on three popular forecasting error measures, namely the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Symmetric Mean Absolute Percentage Error (SMAPE)[24]. Since the smaller value of any measure corresponds to the better forecasting accuracy, the following results represent the evolution from classical statistical approaches to deep learning ones.

Firstly, the ARIMA model produces the highest error values, where RMSE = 12.45, MAE = 10.23, and SMAPE = 18.65%.

Secondly, the SARIMA model shows improved results in comparison with ARIMA, which is represented by RMSE = 10.82, MAE = 8.71, and SMAPE = 15.94%. The use of seasonal components improves the forecast performance in comparison with the classical ARIMA model.

Thirdly, the standard LSTM model achieves lower errors than the previous models, as shown by RMSE = 7.30, MAE = 5.90, and SMAPE = 11.48%. The obtained results demonstrate the ability of LSTM to identify nonlinear dependencies in time series.

Lastly, the proposed LSTM with Attention Mechanism produces the lowest error values compared to other models; it includes RMSE = 5.75, MAE = 4.62, and sMAPE = 8.93%. In comparison with the standard LSTM, the proposed algorithm reduces RMSE from 7.30 to 5.75, MAE from 5.90 to 4.62, and SMAPE from 11.48% to 8.93%.

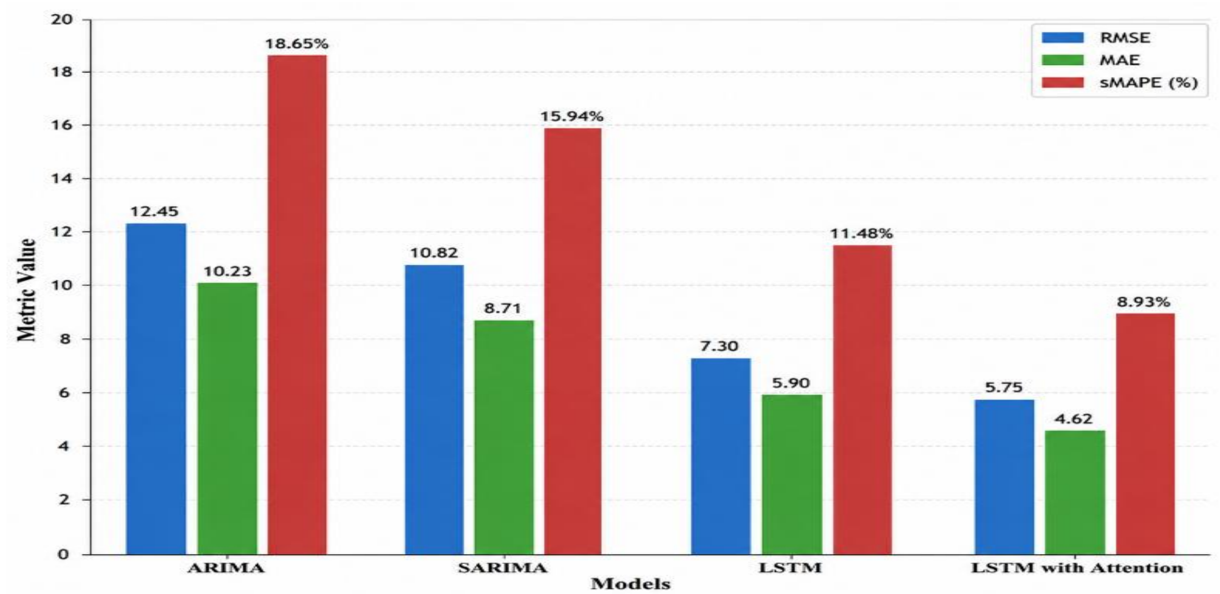

Figure 1. 1 Comparative performance of ARIMA, SARIMA, LSTM, and LSTM-Attention Mechanism based on RMSE, MAE, and SMAPE.

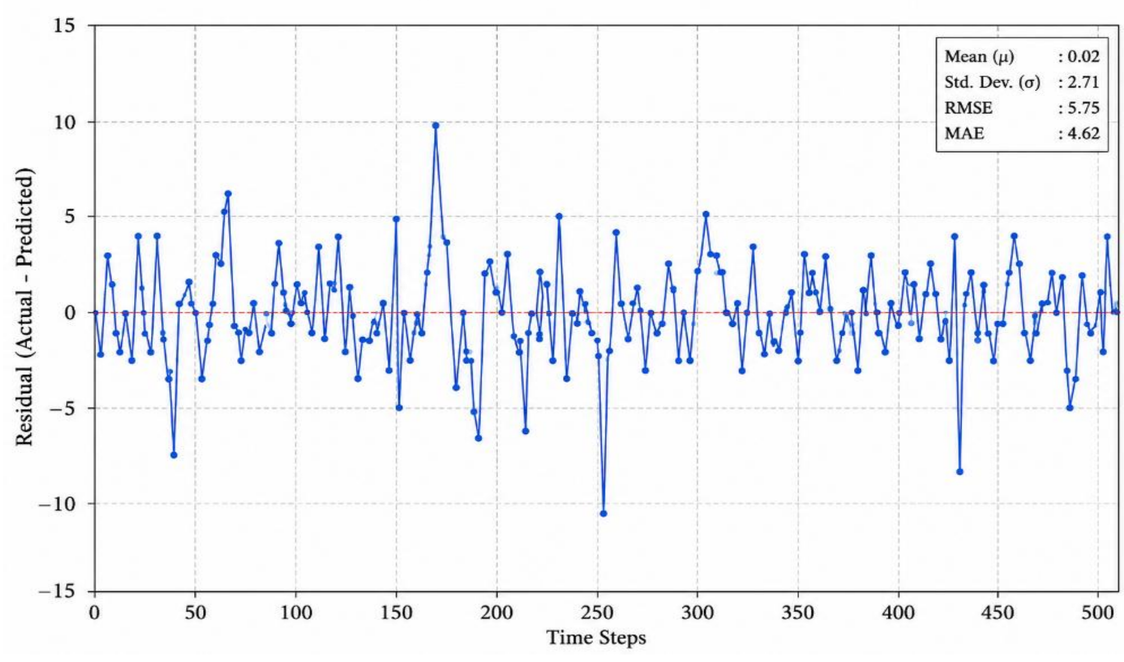

Figure 2. Residual error analysis of the proposed LSTM -Attention Mechanism across the test time steps.

Residual error distribution for the developed LSTM with the Attention mechanism is shown in Figure 2. Residual errors can be defined as follows:

$$et=yt-y\hat{}t \qquad (1)$$

where yt represents the actual value and y^t denotes the predicted value at time step t

It can be seen from Figure 2 that most of the residuals are located near the zero error line, which means that the proposed model is not biased by any particular trend and the proposed approach does not show any systematic deviations in predictions. Mean residual error is about 0.02, which is a very close value to zero. Thus, the predictions have nearly equal positive and negative deviations, without any significant under- or overestimation of the target variable.

However, it should be noted that there are some isolated time steps that have positive or negative deviations. They might occur because of any sudden changes or specific behaviour of the time series. Nevertheless, it is still possible to see that the overall residual distribution has a central tendency around zero.

In addition, according to Figure 2, the MAE is 4.62, and the RMSE is 5.75. It means that the magnitude of the errors is rather small on average; however, the RMSE value is greater due to larger errors. In general, there are relatively few large residuals in comparison with the total number of observations. Therefore, it can be stated that the proposed architecture provides stability of forecasts in the testing period.

8. CONCLUSION

Forecasting using Attention-LSTM networks is a noticeable trend in forecasting research. The Attention-LSTM network can resolve the problems of nonlinear data and long dependencies usually inherent in ARIMA and other traditional forecasting methods since this model can give appropriate weighting of the time steps of the sequence. Because of its high efficiency and interpretability, this model is applicable to financial forecasting, load forecasting, and smart farming, etc. In the future, research related to forecasting should focus on algorithm development aimed at lowering the computational complexity and memory needed to train Attention-LSTM models. In addition, it is necessary to study how distributed computing can improve the training of Attention-LSTM models. Besides, it is important to personalize Attention-LSTM models depending on the nature of the forecasting area. Specifically, there is a need to develop models with regard to the peculiarities of time series in various fields, such as health care, agriculture, and environmental monitoring, etc. The improvement of model explainability for practical application is also very important. Attention-weighting approaches that can help to improve the process of assigning appropriate weights can be used. Furthermore, the possibility of using Attention-LSTM models together with other technologies, such as IoT and cloud computing, deserves attention. The combination of features of such models can help to create more efficient forecasting models for smart farming and energy management.

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