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ARIMA vs LSTM on NASDAQ stock exchange data

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Abstract

This study compares the results of two completely different models: statistical one (ARIMA) and deep learning one (LSTM) based on a chosen set of NASDAQ data. Both models are used to predict daily or monthly average prices of chosen companies listed on the NASDAQ stock exchange. Research shows which model performs better in terms of the chosen input data, parameters and number of features. The chosen models were compared using the relative metric mean square error (MSE) and mean absolute percentage error (MAPE). Selected metrics are typically used in regression problems. The performed analysis shows which model achieves better results by comparing the chosen metrics in different models. It is concluded that the ARIMA model performs better than the LSTM model in terms of using just one feature – historical price values – and predicting more than one time period, using the p, q parameters in the range from 0 to 2, Adam optimizer, tanh activation function, and 2xLSTM layer architecture. The longer the data window period, the better ARIMA performs, and the worse LSTM performs. The comparison of the models was made by comparing the values of the MAPE error. When predicting 30 days, ARIMA is about 3.4 times better than LSTM. When predicting an averaged 3 months, ARIMA is about 1.8 times better than LSTM. When predicting an averaged 9 months, ARIMA is about 2.1 times better than LSTM.

Keywords: Time Series Analysis; Forecasting; Nasdaq; Autoregressive Integrated Moving Average; ARIMA; Long-Short Term Memory; LSTM.

1. Introduction

Nowadays, we can observe that almost every field of science and its applications is becoming increasingly computerized and automated. The COVID-19 pandemic has become a significant accelerator of this process [9, 16]. There are industries which, without IT solutions, are no longer able to function properly. One of the most important areas of this type is finance, equated with the standard of living of households and the prosperity of companies. Regardless of whether it is a legal form or an individual, everyone wants to maximize profits. The financial market offers many

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products to achieve this goal, such as savings accounts, deposits, mutual funds, currencies, bonds and financial instruments such as shares. Each of them is characterized by a specific risk of losing funds. The highest is in the case of stock trading and its amount is proportional to the possibility of achieving large profits in a short period of time [4]. This factor makes stock trading an important source of income for many investors.

The ability to predict future share prices is important not only for investment decisions, but also when planning a company's development strategy, selecting partners for cooperation, and for financial analysis of the company. Each investor makes the decision to buy or sell based on certain information, knowledge or intuition [26]. With different indicators at our disposal [15], it is possible to make more rational decisions. There are many tools on the IT market to support making investment decisions. The most commonly used tools are IT systems implementing technical analysis indicators [7], which, based on historical data, present the way in which stock prices are shaped on charts. Along with the development of statistical models and machine learning, they are used increasingly often in predicting stock prices. In forecasting trends [25], the use of artificial neural networks – a field inspired by biological models – is also becoming increasingly popular. Time series prediction is a topic that is under constant development and requires a lot of research. Some of the latest research in this field was performed by Mateńczuk et al. [21] and Khang et al. [13, 14].

The goal of this paper is to compare two very different models – a statistical one (ARIMA) and a deep learning one (LSTM) – using a very broad and representative range of NASDAQ stock exchange data, to find which model performs better in the problem of time series forecasting. A forecast refers to a calculation or an estimation that uses data from previous events, combined with recent trends to come up with a future event outcome. On the other hand, a prediction is an act of indicating that something will happen in the future with or without prior information [18]. Time series are series of numerical data in which each observation is directly related to a given point in time [6]. In this article, the daily and monthly average stock prices are time series. The field of time series research is in fact about drawing conclusions based on observations about the parameters of the process that generates the data. It makes it possible to predict future values and a forecast error.

To go through the appropriate comparison of the ARIMA and LSTM models, it was decided to conduct a series of experiments on selected data. Three main goals were taken into consideration. They were to find the best ARIMA model, to obtain the best LSTM model and finally to compare the selected models and determine which one is most accurate at predicting stock prices. At the beginning, the focus was on building both models separately, without testing the parameters. The main goal of this stage was to make the models work properly and not cause errors. The relevant parameters were then tested separately using the ARIMA model and different LSTM architectures. The final stage of the work was to create a program to perform of all the experiments and automatically save the results based on the created convention. An important step was also to select the appropriate accuracy measures, thanks to which it was possible to correctly compare the results of the built models. Each step was implemented using the Python programming language.

The rest of the paper is structured as follows. Section 2 outlines the research methodology. Section 3 discusses the significance and relevance of the results. Section 4 concludes the results and briefly specifies the future work directions.

2. Methodology

2.1. Input Data

For the purposes of the analysis and modeling, nine of the most popular NASDAQ sectors, namely: IT, automotive, financial, logistics & transport, clothing, food, energy, healthcare, and entertainment & media, were selected. In the adopted methodology, inspiration was taken from the approach used by [23]. Each sector includes the share prices of 10 companies. Particular attention was paid to the fact that the training model should cover stock prices from various sectors to avoid overfitting.

In the technology sector, very large enterprises have been selected that operate globally and have a real impact on the fluctuations of trends in technology. The list includes both companies related to the production of software and the production of computer hardware. A social network was also selected for this sector (See Table 1).

In the automotive sector, it was also decided to select companies that represent a cross-section of the situation on the market. Companies with a long tradition have been added to companies with modern electric technologies. Companies

Table 1. Stock portfolio selected as the input data. Source: [3].

Sector	Stocks	Total Cap [billion $]
IT	Microsoft, Google, IBM, Zoom, Intel, Facebook, Amazon, Qualcomm, Workday, Logitech	6676
Automotive	Ford, Ferrari, Volkswagen, Toyota, Honda, BMW, Li Auto, Paccar, Kandi, Workhorse	659
Financial	JP. Morgan, VISA, Bank of America, Morgan Stanley, Accenture, Bank OZK, The Carlyle Group, Paypal, Northern Trust Corporation, LPL Financial Holdings	1753
Logistics & Transport	UPS, Boeing, Uber, Vroom, Ryanair, United Airlines Holdings, Sky West, Booking Holdings, ArcBest, Lyft	507
Clothing	Poshmark, HM, JOANN, Weyco Group, Cintas Corporation, Crocs, Columbia Sportswear, Steven Madden, Urban Outfitters, Stein Mart	86
Food	PepsiCo, McDonald's, Unilever, Starbuck, s, Keurig Dr Pepper, The Kraft Heinz, JJ Snack Foods, Sprouts Farmers Market, Pilgrim's Pride, Beyond Meat	760
Energy	Diamondback Energy, APA, PAA Plains All American Pipeline, BP, PDC Energy, Oasis Petroleum, Plains GP Holdings, Weatherford International, Centennial Resource Development, NextDecade Corporation	163
Healthcare	Seagen, BioNTech SE American, IDEXX Laboratories, Sanofi ADR, AstraZeneca, Moderna, DexCom, Natera, Masimo Corporation, ABIOMED	553
Entertainment & Media	Warner Music Group, Fox Corporation, Dish Network, ViacomCBS, Lamar Advertising Company, News Corporation, Nextstar Media Group, iHeart Media, Scientific Games Corporation, Roku	136

from the financial sector constitute a very large percentage of companies on the US NASDAQ stock exchange. The list of companies includes banks and corporations. There were also companies closely related to the financial sector that deals with payment processing. In the logistics and transport sector, both land and air transport were included. These sectors also include companies offering freight. A company closely related to an industry that affects the entire logistics and transport sector was also added to the list. The clothing sector includes recognizable brands whose products are worn by millions of people every day. The food sector includes companies producing food and beverages. The energy sector includes companies dealing not only with oil and gas extraction, but also companies responsible for its distribution and elimination of negative effects on the environment. The selected 10 companies from the healthcare sector include companies producing drugs, vaccines, devices, and technologies necessary in the treatment of patients. The entertainment sector includes companies that reflect the entire media market. The list of companies includes television stations, radio stations, publishing houses and a company producing multimedia equipment.

Each company is identified by its ticker. The ticker (ticker symbol), sometimes called the stock symbol, is an abbreviation used to uniquely identify publicly traded shares of a particular stock company. It can consist of letters, numbers or combinations of both. Most stock symbols on the NASDAQ are unique 4-letter identifiers. Investors and traders use the stock symbols to place trade orders [10].

Sample input data after cleaning is shown in Table 2. It consists of two columns: timestamp and price. Timestamp is the continuous series of the given days, from the period from the year 2008 to 2021. Here, the price is the average price of the particular stock from the given day and is calculated as the average price from all transactions that occurred on that day.

Table 2. Sample of the cleaned IBM stock price data. Source: [24].

Id	Timestamp	Stock Price
1	2008-01-02	105.24647
2	2008-01-03	104.91873
3	2008-01-04	101.84878

After the literature review, it was noticed that in some stock price prediction papers [1, 17], only the closing price was taken into consideration. An example was taken from [1], in which only the closing price was selected for prediction, due to the fact that this price reflects all actions of the stock index during one day. After looking at other scientific literature about stock prices [32, 34], it was noticed that although the closing price is used in a lot of articles, the average price is technically acceptable as well. For technical reasons, especially in the neural network model, the daily average price is better than the daily closing price, because it helps to reduce the noise in the data. It is more resistant to outliers, which may happen at the end of the day. Thus, the average price was chosen rather than the closing price. It was also decided to perform experiments with two types of data (daily and monthly).

2.2. Computational Models

2.2.1. ARIMA model

The basic model in the time series analysis is the ARIMA model. It is a combination of two processes – autoregressive (AR) and moving average (MA), which is weighted delayed random components. The letter I in the model name indicates the level of integration of the analyzed variable. Integrated variables are variables that can become stationary through differentiation. The structure of ARIMA is based on the phenomenon of autocorrelation. ARIMA can be used for modeling stationary time series or non-stationary time series that can become stationary through differentiation. Stationary series are those whose expected value and variance do not change over time, the series values themselves do not deviate from the initial values, and the value of the covariance for two observations depends on the spacing between them, not the timing of their origin. The universal notation $ARIMA\ (p, d, q)$ is used to describe the form of the ARIMA model. The letter p is the order of the regression, d is the order of differentiation and q is the order of the moving average. The process of building the ARIMA model can be divided into three phases, which follows the Box-Jenkins method. In the first phase, identification, the characteristics of the analyzed time series are checked. A decision is made about the need for data to transform and differentiate the series to stabilize its mean, variance covariance. This is done by both examining the autocorrelation function (ACF) and partial autocorrelation (PACF), and by performing statistical Dickey-Fuller and Augmented-Dickey-Fuller tests. In the second phase, estimation and tests, the parameters of the selected models are estimated. The final model selection is usually based on the analysis of several criteria – the significance of model parameters, error metric and information criterion (Akaike's Information Criterion, Bayesian Information Criterion). The next step is a diagnostic check. The properties of a number of model residuals are analyzed. If the residuals of the model are a white noise process, and there are no significant ACF or PACF values of a series of model residuals, the model can be used for forecasting. Otherwise, the estimation and testing phases should be repeated, and a different model should be selected. In some cases, it may be necessary to return to the identification phase. In the third phase, the model is used to prepare a forecast ([20]). The forecast is performed using in-sample and out-of-sample periods. The given dataset is split into an in-sample period, used for the initial parameter estimation and model selection, and an out-of-sample period, used to evaluate the forecasting performance. Empirical evidence based on the out-of-sample forecast performance is generally considered more trustworthy than evidence based on the in-sample performance, which can be more sensitive to outliers [8].

To obtain the desired level of stationarity of the series, all of the input data was logarithmized.

2.2.2. LSTM model

A historic scientific paper published in 1943 [22] initiated a new field of research called artificial neural networks (ANNs). The mathematicians presented an artificial neuron – a model of a nerve cell – and linked its operation to data processing. Since then, the field has been constantly evolving. Hebb discovered in 1949 [11] that information can be stored in the structure of connections between neurons and proposed a new method of learning ANN consisting in changing the connection weights between neurons. The word "Perceptron" was proposed by Rosenblatt [28], who together with Wightman built a neural-like network. It was part electronic, part electromechanical and was used to recognize alphanumeric characters. It was the first physical and functional machine of this type. The above achievement led to the spread of interest in neural networks and research on them all over the world.

Recursive neural networks (RNNs) are a broad class of networks in which, even as the input data changes over time, the same parameters are used. Recursive networks are among the most successful models that are devouring applications both in research and industry to problems related to sequential data in natural language processing, time series prediction and classification. The main differences between unidirectional and recursive networks are that RNNs see the time data in an ordered form as values in successive steps and have a state that is preserved between successive time steps. It is this state, as well as its static parameters, that are responsible for updating the network response after providing it with new information in the next steps. The disadvantage of RNNs is that they suffer from short-term memory. One of the solutions to that problem is a model introduced by Hochreiter and Schmidhuber [12] called long short-term memory (LSTM). It is capable of learning long-term dependencies using a mechanism called gates, which are different tensor operations that can learn what information to add to or remove from the hidden state. A comparison of a single unit of a classical RNN with an LSTM is presented in Figure 1.

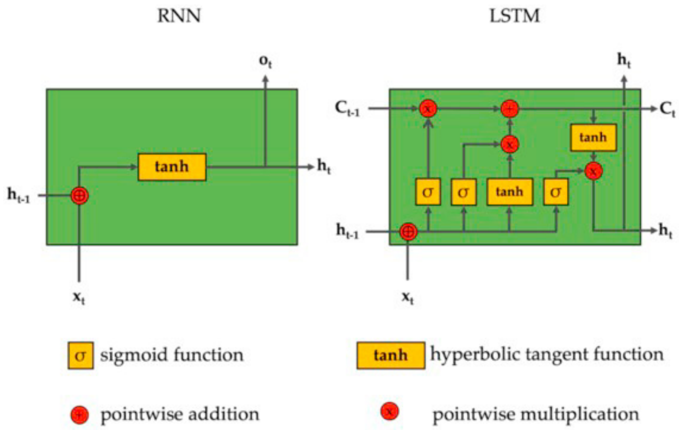

Fig. 1. RNN and LSTM comparison [30]

To compare the ARIMA and LSTM models, there is a need to choose the best one in each case in relation to the selected performance metrics. The comparison of predicted values was performed with exactly the same input data processing. The data was logarithmized and fitted to the models in daily or monthly intervals. In the case of LSTM, the data was also normalized according to the input set and divided into several input and output windows, moved by a fixed shift. In the case of ARIMA, every company time series was processed as a whole.

2.3. *Output Data*

The output data for both models is the time series prediction for a given time window.

In the case of the ARIMA model, it is a table consisting of rows containing: company ticker, real value from out-of-sample period, prediction value, standard error, and lower and upper value boundaries resulting from the calculation +/- 2*standard error. To obtain the prediction values in US $, the mathematical exponential operation must be performed (values were previously log-transformed). Exemplary prediction results for the IBM company are shown in Table 3.

Table 3. IBM exemplary prediction results (ARIMA model)

company	real_value	prediction	standard_error	lower_series	upper_series
IBM	4.897324	4.900446	0.010132	4.880588	4.920305
IBM	4.896517	4.896496	0.010131	4.876639	4.916353

In the case of the LSTM model, the output data is a table consisting of: x_test – fragment of the company time series (whose length is defined as the input window size) used by the model to predict future values; y_predict – time series predicted by the model (length defined as the output window size); y_test – real values of the time series in the predicted period, used to check the model performance; company_name – ticker of the predicted company; x_start_date, x_end_date – start and end date for the x_test set; y_start_date, y_end_date – start and end date for the y_test and y_predict sets. Exemplary prediction results for the IBM company are shown in Table 4.

Table 4. IBM exemplary prediction results (LSTM model)

company_name	x_start_date	x_end_date	y_start_date	y_end_date
IBM	2011-04-16	2011-10-12	2011-10-13	2011-11-11

x_test	y_test	y_predict
165.18612473	186.49382407	186.22127266
164.56847636	189.29697533	186.16533308

3. Results and Findings

It was decided to compare the models using 3 different periods: 30 days, 3 months and 9 months. The main reasons were to reflect various investment opportunities (short-, medium- and long-term) and that everyone has their own investment preferences: the goal was to aim the research in the direction that makes business sense and is useful for various types of investors. A further two basic comparisons were performed: 1 day, and 1 month, to check if LSTM or ARIMA performs better in the case of a prediction just 1 step ahead.

Table 5. Comparison of MAPE for ARIMA and LSTM for different time windows

time window	ARIMA (MAPE)	LSTM (MAPE)
1 day	1.64	**1.46**
30 days	**1.64**	5.52
1 month	**4.28**	6.90
3 months	**5.93**	10.53
9 months	**7.55**	16.05

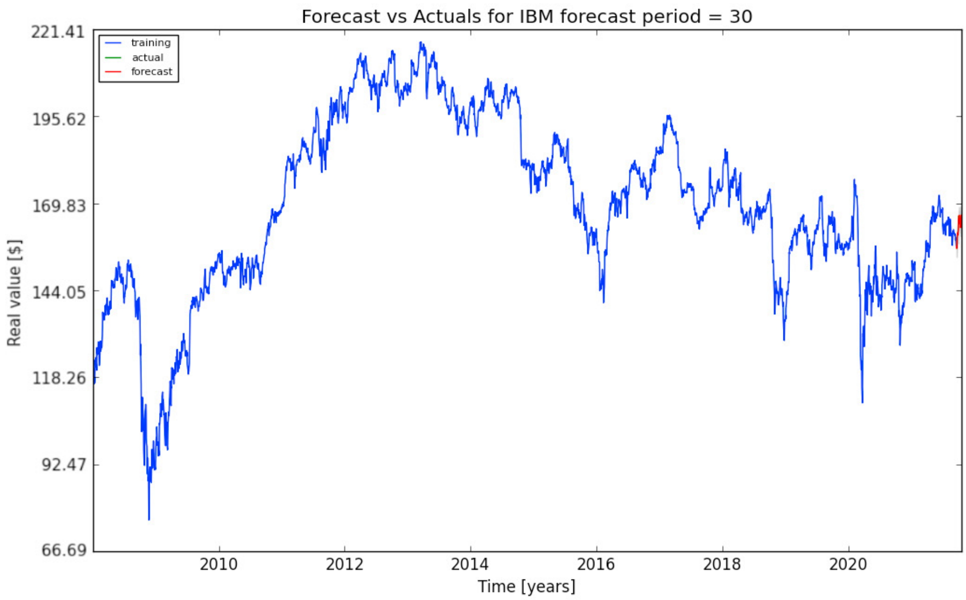

Fig. 2. Prediction for IBM company using ARIMA, 30-day period

Two types of errors were selected to compare the performance of each model separately and to compare both models against each other – Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE). The results of

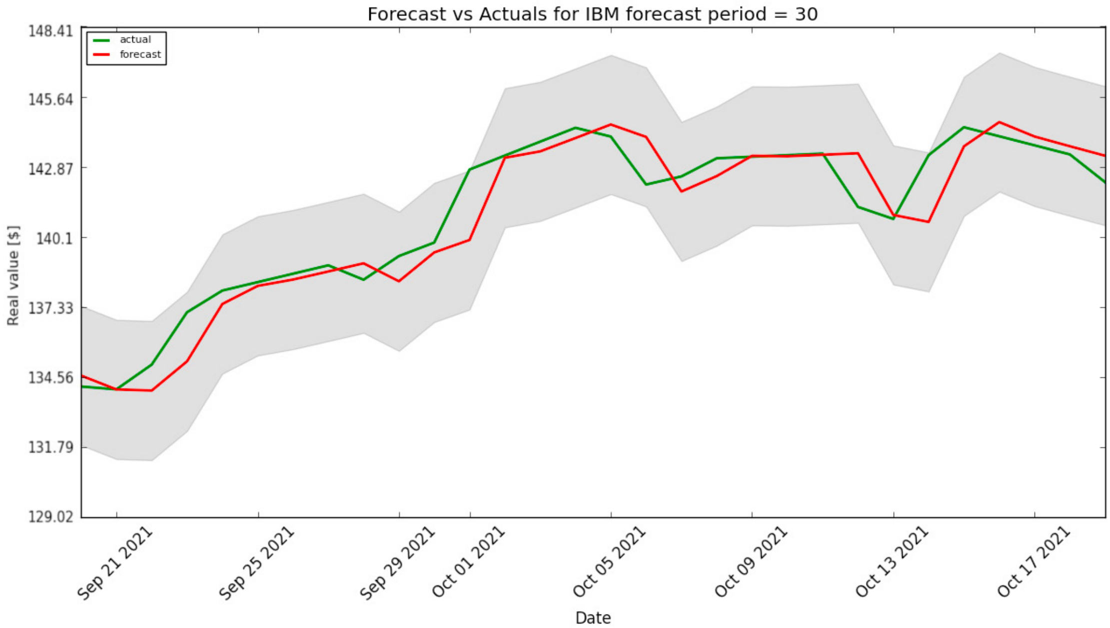

Fig. 3. Prediction for IBM company using ARIMA, 30-day period (zoomed)

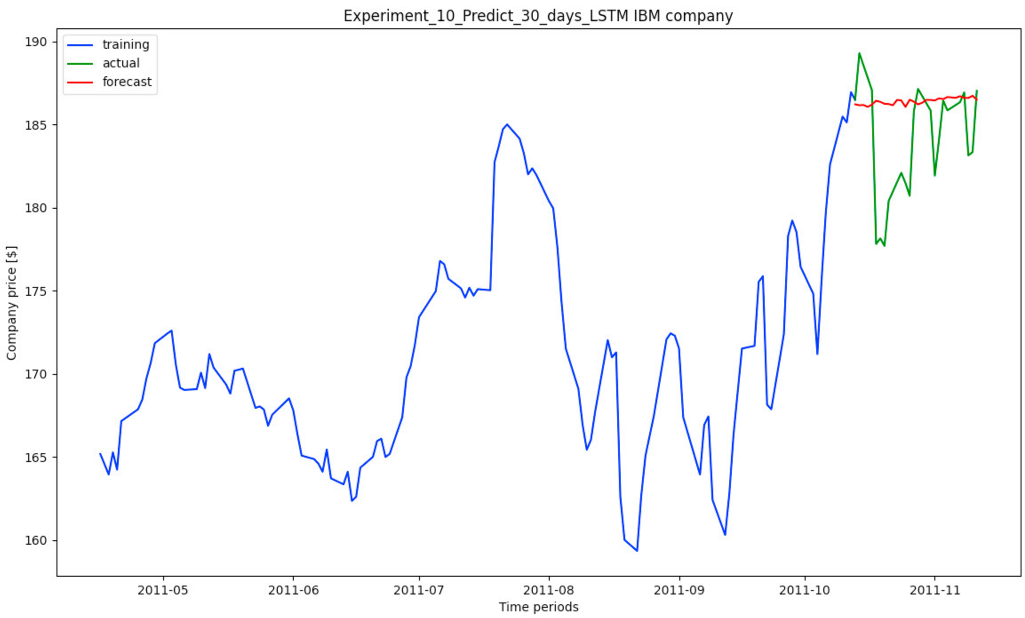

Fig. 4. Prediction for IBM company using LSTM, 30-day period (zoomed)

the experiments carried out for the ARIMA model showed that the p and q ranges should be restricted to values of 0, 1 or 2. The results of the LSTM model experiments showed that the best parameters for the neural network model are

2xLSTM architecture, Adam optimizer and tanh activation function. The next experiments were therefore carried out using these parameters. A comparison of the GRU and LSTM architectures was also performed, which showed that in the case of the selected data, the GRU architecture performs worse than the LSTM.

The experiments performed to choose time windows for LSTM showed that the best input window sizes for LSTM are 180 days in the case of daily intervals and averaged 1800 days in the case of monthly intervals.

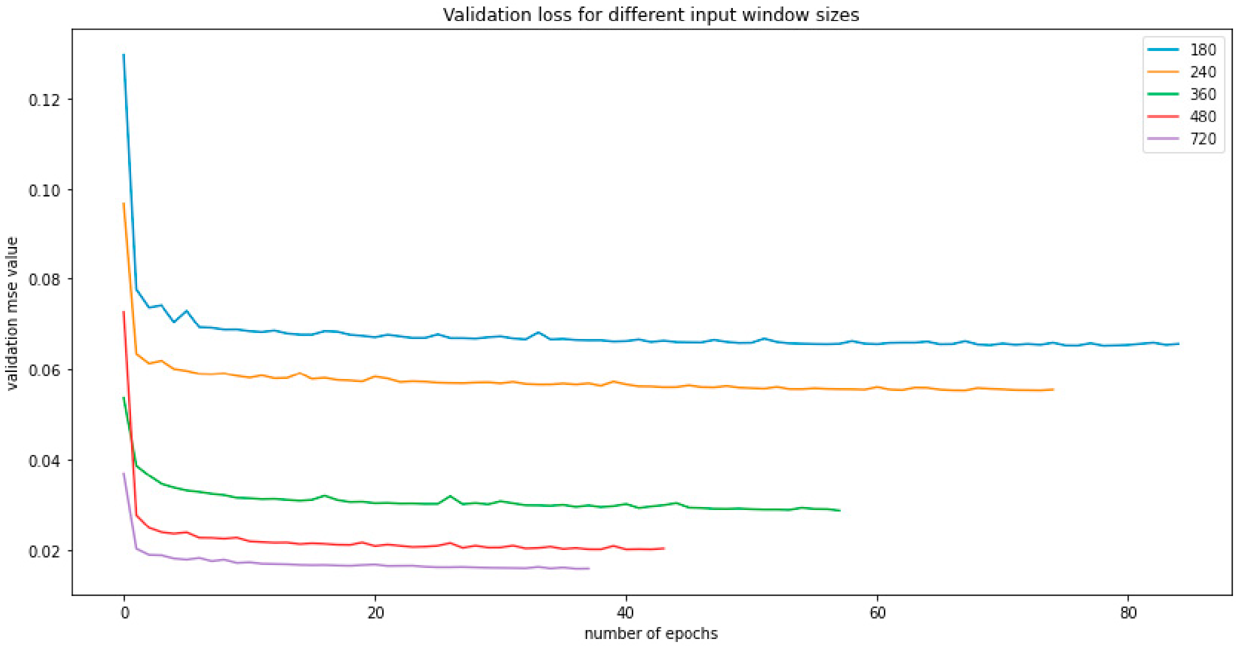

Fig. 5. Validation loss values for different input window sizes

The further conducted research showed that in most cases, ARIMA performs better than LSTM (according to the comparison of the MAPE error values). When predicting 30 days, ARIMA is about 3.4 times better than LSTM. In the case of predicting averaged 1 month, ARIMA performed about 1.6 times better than LSTM. When predicting averaged 3 months, ARIMA is about 1.8 times better than LSTM. When predicting averaged 9 months, ARIMA is about 2.1 times better than LSTM. LSTM only performed better in the case of 1-day prediction (about 1.12 times better). It can therefore be concluded that the longer the period, the better ARIMA performs and the worse LSTM performs (the ARIMA results confirm the results obtained by Wang et al. [31]). Based just on the price feature, the ARIMA model is better at calculating the next predictions. The achieved results confirm the results found by Yi-Tou et al. [2]. A comparison of the achieved MAPE results for ARIMA and LSTM for different time windows is shown in Table 5.

Learning plots showed that LSTM is not learning (after the 5th epoch, an example is shown in Figure 5). The reason of this behavior is that not enough features were taken into account (just one feature was used – price). In LSTM, all of the desired prediction period values are predicted at once. That is why LSTM produces worse results– it consists of a more complicated architecture which needs more features for effective training. Otherwise, the LSTM model is in its basic state and is not using its full potential. The colors used are not important in Figure 5 and only serve to make it easier to distinguish between different time windows. In the case of predicting the stock prices of NASDAQ-listed companies using just historical price values (single feature), the statistical model (ARIMA) achieves better results than the deep learning model (LSTM).

A comparison of the ARIMA and LSTM sample prediction results for the 30-day prediction periods for the IBM company are shown in Figures 2, 3 and 4. Colors used: blue indicates historical company prices (used by the models either to learn in the case of LSTM or as the in-sample period in the case of ARIMA); red indicates the forecast performed by the model; green indicates the company's real future prices (used to calculate the error between the forecast and the actual values).

4. Discussion, Future Research and Limitations

During the comparison of the ARIMA and LSTM models, the logarithmized data were used in both the ARIMA and LSTM models. This decision is confirmed by the research conducted by Hoque et al. [27] and Dezsi et al. [5]. In the ARIMA model, the logarithm operation was necessary to achieve time series stationarity; however, in the case of LSTM, it was possible to check if the network can achieve better results using the data without the logarithm operation. Also, some other methods of sample generation may be tested.

The main value of the presented research is that the model comparison is performed on a very broad and representative dataset from the NASDAQ stock exchange. It covers the most important sectors of the US economy. The comparison of models was done to create a solid background for the usage of ARIMA and LSTM models in time series prediction. The achieved results can be developed in further research to explore the neural network aspect in more depth.

It would be valuable to check if the LSTM model with multiple features can outperform the ARIMA model, which is based just on the price feature. This is very probable according to the research performed by Namin et al. [29], in which the data consisted of monthly financial time series of five stock indices and monthly economics time series from the Federal Reserve Bank of St. Louis and the International Monetary Fund Website, so there was a significant number of features used in LSTM model. The results showed that the deep learning model performs much better than the statistical model.

When choosing LSTM features, sentiment analysis can be used in addition to economic indicators. Such an approach, with the usage of sentiment downloaded from news feeds, may help to achieve an interesting model, which will be able to predict sudden spikes in prices and stock market crashes. Research in this area was performed by Wojarnik [33]. The overriding feature of recursive LSTM networks is that multiple variables can be used as input. Unfortunately, this is not possible with the ARIMA model. The research area currently under development [19] is a hybrid model in which autoregression and deep learning networks are used at once. The use of the benefits of both types of models while leveling their disadvantages can significantly improve the quality of prediction. This area requires more detailed research.

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