The Application of SISO LSTM Networks to Forecast Selected Items in Financial Quarterly Reports – Case Study

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Abstract. Automatic analysis of financial data is the subject of many ongoing research. The aim of this study was to explore deep learning methods to predict and forecast the value of selected financial data included in financial quarterly reports based on historical data in a given future horizon, assuming incomplete data. The study considered the quarterly financial reports of selected companies listed on the Warsaw Stock Exchange (WSE), in the period from September 2010 to December 2021, where each report consists of about 250 indices. Basing on the principles of financial analysis and the interdependencies between financial indicators, a selection of interdependent indicators has been established to forecast future indices values based on historical data. The reinforced learning technique was used to see if it improves forecast results relative to the classic deep learning technique. Results indicate good prediction of the financial statement values up to one-year horizon, i.e., up to four future quarterly reports, considering both complete and incomplete financial data. Also, it is shown how observation update (reinforced learning) influences the forecast result. Forecast results are supporting tool for financial analysis for WSE.

Keywords: Automated reasoning · Time series analysis · Forecasting · Ai-supported simulation · Financial indices · Financial report analysis · LSTM network

1 Introduction

Financial forecasting is an increasingly used tool in corporate finance management. Since forecasting allows for rational and scientific forecasting of future events, it allows making decisions (e.g. investment decisions) with the possibility of relatively precise

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estimation of their impact on the financial situation of the enterprise. This is essential in the economic realities where economy practitioners more and more often use data from financial statements and financial analysis to make decisions based on them. Preparation of a financial forecast is associated with the need to accept the uncertainty it carries with it. However, even though making an accurate forecast (due to the presence of random factors that cannot be taken into account at the stage of forecast preparation) is extremely difficult, it allows for a detailed analysis of the company's future financial situation and taking into account elements that are not taken into account during the standard analysis financial (Franc-Dąbrowska and Zbrowska 2008). Thus, it enables a more detailed identification of opportunities and threats in the financial sphere of the company's operation. Therefore, it seems that financial forecasting will be increasingly used in economic practice, especially in entities operating on international or global markets, as a supplement to traditional methods of financial analysis. The basic methods of financial analysis require supplementation. Summarising, there is a need to develop practical methods that allow for a relatively simple forecast of the company's financial situation in the perspective of at least several financial reports ahead, which is not easy due to the complexity of forecasting methods and the occurrence of random factors, impossible to predict when building the forecast.

Along with the development of data collection tools, there are solutions that allow for their analysis, i.e. digital platforms that provide automated financial planning services, based on algorithms and hardly supervised by man. This type of platform obtains information about the financial situation and future goals from the client point of view. Then, it uses such data to provide consulting services (using, among others, data from reports) and automatically investing client funds. Artificial intelligence (AI)and especially deep learning is increasingly being used in data analysis, and 70% of companies are already declaring in their research that they intend to introduce AI-based solutions in nearest future. The newest research (e.g. Hedayati et al. 2016; Burba 2019) indicates that AI techniques based on deep learning are useful in analysis of stock market indicators, successfully extending classical approaches based on technical analysis.

Many existing implementations of deep learning in financial area are focused on forecasting on a given financial series (Korczak and Hemes 2017; Sezer et al.2020; Mateńczuk et al. 2021). The main focus is on predicting the next movement of the asset – including stock price forecasting, index prediction, forex price prediction, commodity price prediction, bond price forecasting, volatility forecasting, cryptocurrency price forecasting. Relatively little attention is paid to the analysis of financial data contained in periodic reports, ie annual and quarterly.

One of the most frequently applied deep learning method in financial time series forecasting is LSTM (e.g. Chen 2015; Zhao et al. 2017; Roondiwala et al. 2017; Qiu et al. 2020; Fischer and Krauss 2018; Galuszka et al. 2020a, b). However, some initial decisions when applying AI in stock index analysis need to be made. They are connected e.g. with time window of analysed data, since improper choice of it may lead to unsatisfactory results and similar difficulties are met in any time-series domains (Kyoung-jae 2003; Shumway and Stoffer 2017).

The paper is organized as follow: in next section aim, methods and scope of the research is formulated, in Sect. 2 methodology is presented, in Sect. 3 forecasts results are shown. All is concluded in Sect. 4.

1.1 Aim, Methods and Scope of the Research

In the paper we are focused on financial quarterly reports. The aim of the work is to prepare and evaluate the forecast of a set of selected basic financial statement items included in financial quarterly reports:

- revenues from sales
- operating profit/loss
- net profit/loss attributable to equity holders of the parent
- total comprehensive income attributable to equity holders
- depreciation
- assets
- non-current assets
- equity shareholders of the parent

for a selected group of companies representing enterprises of various types with different behaviors, listed on WSE. Results of the work are expected to be a supporting tool in analysis of financial reports on WSE.

A set of five companies (limited due to data delivered for tests) with a division into companies dealing with industry, finance and services was used in the study, representing industry, finance and services. The training period covered the years 2010–2020 and the forecast were done for 2021. Intentionally the research does not cover pandemic period since its influence for financial statements was unpredictable.

In the analysis Matlab's DeepLearnig Toolbox (www.mathworks.com) to forecast time series using deep learning has been used. In particular, time series data forecasts using long-short-term memory (LSTM) networks with single input and single prediction (thus SISO structure) has been applied.

2 Methodology

2.1 LSTM Networks

The LSTM network is being developed in order to forecast future index values based on historical data. LSTM networks are a type of recursive neural network (RNN) designed to avoid the problem of long-term relationships, in which each neuron contains a memory cell capable of storing prior information used by RNN or forgetting it when needed (Hochreiter and Schmidhuber 1997). They are now widely used successfully in time series prediction problems (e.g. Elsaraiti and Merabet 2021). The LSTM-RNN is designed with a memory cell that stores long-term dependencies. In addition to the memory cell, the LSTM cell includes an input gate, an output gate, and a forget gate. Each gate in the cell receives the current input, the hidden state in the previous time, and

the state information of the cell's internal memory in order to perform various operations and determine whether to activate using activation function. To predict the values of future time steps of a sequence, it is assumed that the answers are training sequences with values shifted by one time step. This means that at each stage of the input sequence, the LSTM network learns to predict the value of the next time step. To forecast the value of multiple time steps in the future, the PredestAndUpdateState function from the toolbox was used to predict time steps one by one and the network status was updated with each forecast. The training parameters of the network are given in the Table 1.

Table 1. The training parameters of the network

No. of hidden units	200
Solver	Adam
Max epochs	250
Gradient threshold	1
Initial learn rate	0.005
Learn rate drop period	125
Learn rate drop factor	0.2

Input data for the analysis is excel report file, containing 277 financial items published each quarter over 11 years, i.e. size of the data vector for each item is 44 with some missing values. Piece of data is shown in Table 2.

Table 2. Piece of quarterly financial data.

Accounting period	07.01-09.01	10.01-12.01	01.02-03.02	04.02-06.02	07.02-09.02	10.02-12.02
Basic information						
End of period	2001-09-30	2001-12-31	2002-03-31	2002-06-30	2002-09-30	2002-12-31
Start of period	2001-07-01	2001-10-01	2002-01-01	2002-04-01	2002-07-01	2002-10-01
Revenues from sales	233 788	257 077	225 646	215 734	279 438	271 347
Operating profit/loss	21 215	8 235	12 729	5 610	18 500	4 492
Net profit/loss attributable to equity holder	3 331	7 375	2 628	-2 249	5 851	-3 479
Total comprehensive income attributable to equity holders						
Depreciation	16 392	16 058	15 148	15 112	15 308	15 635
Cash flow from operating activities	21 203	20 721	4 442	23 370	18 755	16 179
Cash flow from investing activities	-19 341	-41 770	-4 595	-23 868	-13 619	29 509
Cash flow from financing activities	-743	19 105	13 674	-3 606	-8 574	-50 526
Aktywa	685 879	644 951	695 951	702 836	764 332	727 941
Non-current assets	431 400	413 970	419 617	414 335	404 343	403 693
Current assets	254 479	230 981	276 334	288 501	359 989	324 248
Equity shareholders of the parent	193 066	198 375	188 822	183 735	188 723	220 012
Non-current liabilities	202 526	214 508	216 924	188 476	191 349	176 924
Current liabilities	290 287	232 068	286 635	326 541	380 143	327 786

The output data for our analysis are:

- Statement forecast up to four (4) quarterly periods (up to 1 year),
- Normalized error,
- Statement forecast with observation updates,
- Normalized error of forecast with updates,
- LSTM training progress data.

2.2 Data Preparation

The data in quarterly reports very often were incomplete. There are different methods of replacing missed data with numbers and most often used are: linear interpolation of neighboring, nonmissing values; specified constant value; previous nonmissing value; next nonmissing value; moving median with specified window size or moving mean with specified window size (see e.g. mathworks.com). Without further justification in the research missing data are filled with moving median method with fixed window size. The method returns an array of local k-point median values, where each median is calculated over a sliding window of length k across neighboring elements of A. When k is odd, the window is centered about the element in the current position. When k is even, the window is centered about the current and previous elements. The window size is automatically truncated at the endpoints when there are not enough elements to fill the window (Matlab 2021).

2.3 Error Normalization

The comparison of the forecasts efficiency has been done using the root-mean-square error (RMSE) calculated from the standardized data, i.e.:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{test,i} - X_{pred,i})^2}{n}}, \tag{1}$$

where X_{test} are test values and X_{pred} are predicted values at time i. To be able to compare the forecasts quality RMSE has been normalized in two ways:

1) using the difference between maximum and minimum of the test data:

$$NRMSE1 = RMSE/(X_{test\,max} - X_{test\,min}), \tag{2}$$

2) using the mean (average) of the test data:

$$NRMSE2 = RMSE/(X_{test\,mean}). \tag{3}$$

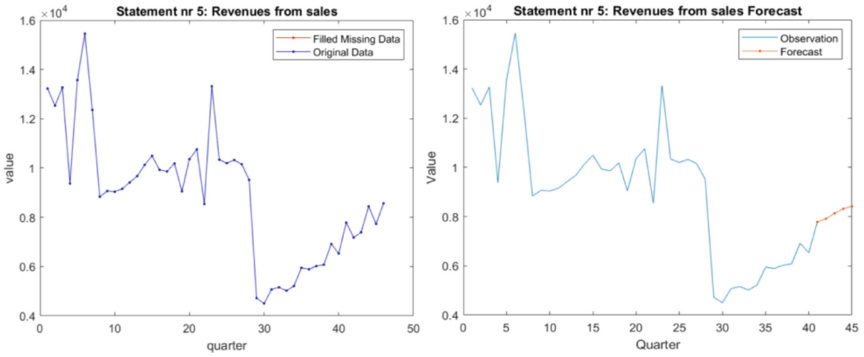

Fig. 1. Revenues from sales data (left) and data with forecast (right)

3 Forecasts

3.1 Example of Forecasts for Industry Companies for Complete Data

The example data file contains a single time series, with time steps corresponding to quarter and values corresponding to financial statement items, here revenues from sales. The output is an array of cells in which each element is a single time step. In the Fig. 1. revenues from sales data and data with forecast are presented.

The Fig. 2 (left) shows the forecasts for the values actually observed along with the prediction error. If actual index values of forecasts is known, one can update the network status with the observed values instead of the predicted ones, thus confronting the learning results with the actual values (the so-called reinforced learning technique). The results are shown in the Fig. 2 (right). In this case, the observation update significantly (not in a statistical sense) improves the prediction result.

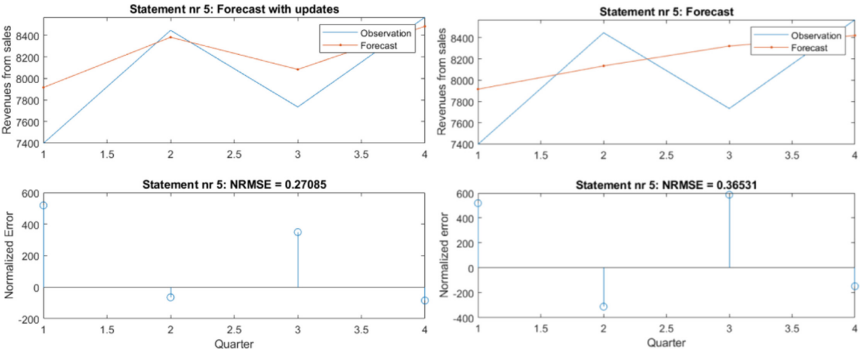

Fig. 2. Revenues from sales forecast with NRMSE (left) and forecast with updates with NRMSE (right)

3.2 Example of Forecasts for Finance Companies for Slightly Incomplete Data

The example data file contains a single time series, with time steps corresponding to quarter and values corresponding to financial statement items, here operating profit/loss. The output is an array of cells in which each element is a single time step. In the Fig. 3. operating profit/loss data and data with forecast are presented.

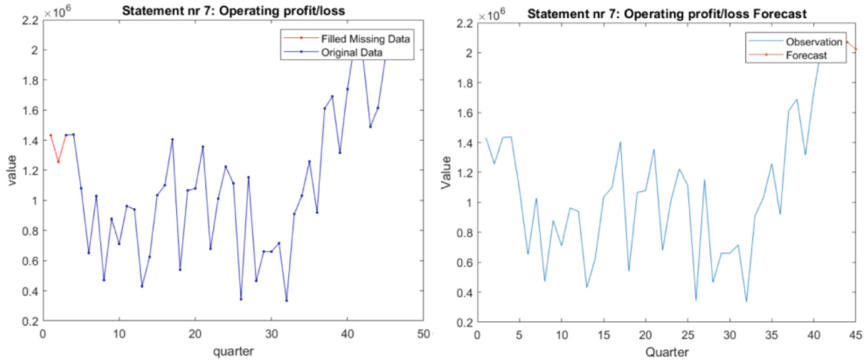

Fig. 3. Operating profit/loss data (left) and data with forecast (right)

The Fig. 4 (left) shows the forecasts for the values actually observed along with the prediction error. If actual index values of forecasts is known, one can update the network status with the observed values instead of the predicted ones, thus confronting the learning results with the actual values. The results are shown in the Fig. 4 (right). In this case, the observation update significantly (not in a statistical sense) worsens the prediction result.

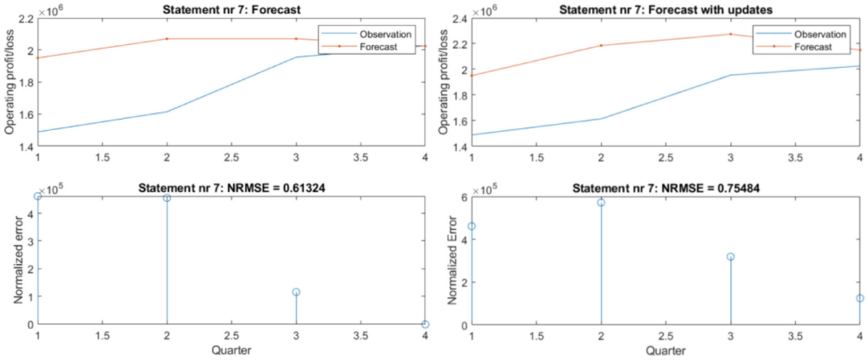

Fig. 4. Operating profit/loss forecast with NRMSE (left) and forecast with updates with NRMSE (right)

3.3 Example of Forecasts for Service Companies for More Incomplete Data

The example data file contains a single time series, with time steps corresponding to quarter and values corresponding to statement values, here cash flow from financing activities. The output is an array of cells in which each element is a single time step. In the Fig. 5 cash flow from financing activities data and data with forecast are presented.

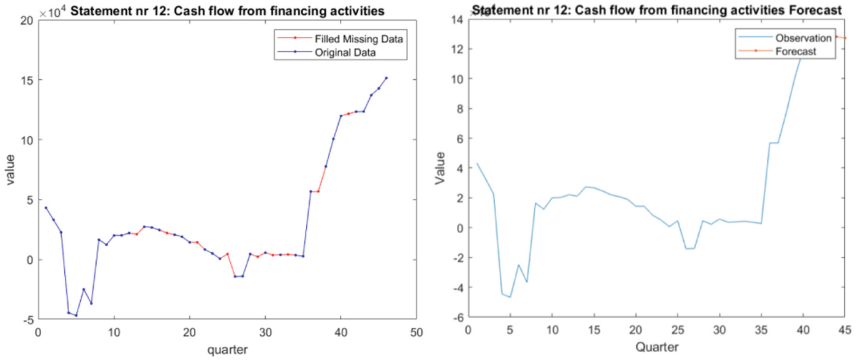

Fig. 5. Cash flow from financing activities data (left) and data with forecast (right)

The Fig. 6 (left) shows the forecasts for the values actually observed along with the prediction error. If actual index values of forecasts is known, one can update the network status with the observed values instead of the predicted ones, thus confronting the learning results with the actual values. The results are shown in the Fig. 6 (right). In this case, the observation update slightly improves the prediction result.

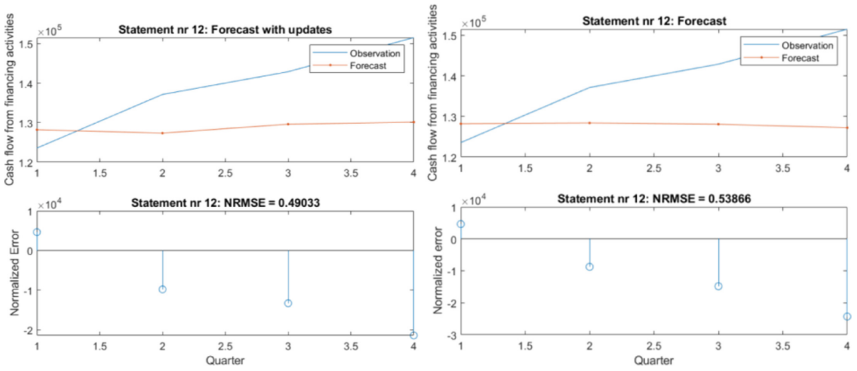

Fig. 6. Cash flow from financing activities forecast with NRMSE (left) and forecast with updates with NRMSE (right)

3.4 Accuracy of Financial Statements Forecast in One-Year Horizon

In Tables 3 and 4 NRSME1 (2) for each analyzed financial statement item and for each considered company are presented. In Tables 5 and 6 NRSME2 (3) for each analyzed financial statement item and for each considered company are presented. Minimal values in each column are marked bold. One should note that for M-LSTM in each case we received significantly lower values for minima of the NRSME, significantly higher values for maxima of the NRSME and similar or even worse NRSME values for averages. We do not include SD parameter due to too few analyzed companies.

Table 3. NRSME1 forecast for each analyzed financial statement item and for each considered company

	Forecast NRMSE1		
Financial statement item	Min	Max	Avg
-revenues from sales	0,3653	0,8165	0,52545
-operating profit/loss	**0,3105**	**0,5923**	**0,4915**
-net profit/loss attributable to equity holders of the parent	0,3457	1,5549	0,77953
-total comprehensive income attributable to equity holders	0,4914	0,8949	0,69375
-depreciation	0,3553	0,8631	0,60553
-assets	0,4824	2,2116	1,22135
-non-current assets	0,6237	2,3993	1,15548
-equity shareholders of the parent	0,4499	0,7359	0,5497

Table 4. NRSME1 forecast with updates for each analyzed financial statement item and for each considered company

Financial statement item	Forecast with updates NRMSE1		
	Min	Max	Avg
-revenues from sales	**0,2708**	**0,5744**	0,44515
-operating profit/loss	0,4205	0,781	0,5638
-net profit/loss attributable to equity holders of the parent	0,3274	10,3016	3,021875
-total comprehensive income attributable to equity holders	0,6024	1,055	0,7548
-depreciation	0,3572	0,8566	0,592867
-assets	0,5015	2,4117	1,2166
-non-current assets	0,5289	2,6683	1,22575
-equity shareholders of the parent	0,487	0,6984	**0,557667**

4 Conclusion and Future Works

The scheme resulting from the multi-criteria optimization for passenger communication analysis - the access point in the vehicle is shown in the Fig. 3.

The results obtained do not clearly indicate the quality of the forecasts and the size of the prediction horizon. The wide range of NRMSE1 and NRMS2 is caused by assumed normalization method, which returns high values of NRMSE in case of not varying test data. The problem is that future values of financial statement items depend not only on past values (except fully determined systems with known excitations and without undetermined disturbances) but also on other external signals that can occur occasionally taking the form of non-time series data (non-predicted market conditions).

Table 5. NRSME2 for each analyzed financial statement item and for each considered company

Financial statement item	Forecast NRMSE2		
	Min	Max	Avg
-revenues from sales	0,0713	1,2949	0,504733
-operating profit/loss	0,0287	1,9763	0,743533
-net profit/loss attributable to equity holders of the parent	0,4639	0,9564	0,7233
-total comprehensive income attributable to equity holders	0,223	48,7909	17,5413
-depreciation	0,0513	0,1394	0,09535
-assets	0,0368	0,2585	0,116767
-non-current assets	0,0334	0,3423	0,2285
-equity shareholders of the parent	**0,0002**	**0,0944**	**0,033**

The forecast result in financial report case should be treated rather as a supporting tool in automatically noting possible unusual changes in financial data reporting than an efficient forecasting tool.

Future works will be focused on:

1) Perform analysis for other simulation scenarios, considering cross-correlations of the data, changing:

   a. methods of missed data management,
   b. forecasting horizon size,
   c. normalization methods.

2) On the basis of performed analysis, indicate the optimal sets of LSTM parameters.
3) The indications should be subject to expert opinions.

Table 6. NRSME2 forecast with updates for each analyzed financial statement item and for each considered company

Financial statement item	Forecast with updates NRMSE2		
	Min	Max	Avg
-revenues from sales	0,076	1,3071	0,511033
-operating profit/loss	0,0267	1,3675	0,537467
-net profit/loss attributable to equity holders of the parent	0,7013	4,3616	2,070567
-total comprehensive income attributable to equity holders	0,1584	36,9211	13,45953
-depreciation	0,0534	**0,1016**	0,0775
-assets	0,0403	0,2687	0,1249
-non-current assets	0,037	0,3008	0,200267
-equity shareholders of the parent	**0,0002**	0,1206	**0,041333**

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