COMPOSITE FINANCIAL PERFORMANCE INDEX PREDICTION – A NEURAL NETWORKS APPROACH

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Abstract. Financial indicators are the most used variables in measuring the business performance of companies, signaling about the financial position, comprehensive income, and other significant reporting aspects. In a competitive environment, the performance measurement model allows performing comparative analysis in the same industry and between industries. This paper aims to design a composite financial index to determine the financial performance of listed companies, further used in predicting business performance through neural networks. Principal components analysis was used to build a composite financial index, employing four traditional accounting indicators and four value-based indicators for the period 2011–2018. Five experiments were conducted to predict business performance through the composite financial index. The results showed that observations from two years, of the first three experiments, indicate a better predictive behavior than the same experiments using observations from one year. Therefore, we concluded that observations from more than one year are necessary to predict the value of the financial performance index. Findings led us to the conclusion that recurrent neural networks model predicted better financial performance composite index when taken into consideration more real data for the financial performance index (2012–2018) instead of just for one year (2018).

Keywords: business performance, financial indicators, composite index, PCA, predictive behaviour, neural networks.

JEL Classification: M21, M41, L25, C45, G39.

Introduction

The financial performance is the essential component of measuring the overall performance of a company. The concern of financial analysts, investors, and managers in finding optimal models for evaluating financial performance is constantly increasing. Thus, in a highly

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competitive business environment, the performance measurement model can make a difference within an industry. Starting from this hypothesis, the study considered that the financial performance evaluation model must consider not only traditional business financial indicators but also value-added indicators. Examining the usefulness of various financial variables in predicting, Estrella and Mishkin (1998) observed that a financial indicator can signal a problem that requires further investigation and analysis. Financial indicators are frequently used tools in predicting business failures and performance, and also are used to develop the prediction models (Huang et al., 2008). Although, many models of financial performance measurement are known, based on the grouping of indicators into profitability, solvency, liquidity, market, value-added indicators, or the use of a single indicator, considered relevant or a group formed out of two or three indicators, in this paper we chose to build a composite financial index based on panel data. Also, predicting company financial performance has been a frequent research issue in the area of business analysis and corporate reporting. Therefore, approaches based on neural networks are increasingly used in the construction of financial performance prediction models, in the last two decades.

In this paper, traditional and value-based financial indicators were used to design a neural network model for predicting the financial business performance of selected listed companies. The prediction model was built considering the composite performance index designed through principal component analysis (PCA) and a neural network approach. This paper presents briefly several previous research contributions on financial performance measurement and business prediction models. They are followed by data collection description, composite index construction methodology, business performance prediction model presentation, analysis of data, and discussion of the recurrent neural network (RNN) results. In the last section, the conclusions and limits are inserted.

1. Business performance measurement and prediction – related works

Through financial indicators, companies' stakeholders can understand the dynamics of their performance and found valuable information related to financial position, comprehensive income, cash flows and changes in equity and also the risks that managers face in their daily business transactions (Song et al., 2018; Elshandidy et al., 2018; Taylor et al., 2014; Li et al., 2017; Bini et al., 2015; Lehavy et al., 2011; Magnusson et al., 2005; Li, 2010). Moreover, financial performance indicators are real barometers of the success of a company. As Beaver (1966) pointed out financial ratios can make the difference between performing and failing companies. Previous studies done by Smith and Taffler (2000), Fields et al. (2001), Zhang et al. (2004), Kloptchenko et al. (2004), Qiu et al. (2014), Badulescu et al. (2020), showed that there is a wide range of ways to measure firm performance. In Kloptchenko et al. (2004), seven financial indicators were selected to characterize and measure a company's performance including, three profitability ratios, one liquidity ratio, two solvency ratios, and one efficiency ratio, while Zhang et al. (2004), used only earnings per share (EPS), to forecast financial performance. Qiu et al. (2014) used EPS, a classical accounting indicator, and size-adjusted cumulative return (SAR), a market response measure, to evaluate a company's financial strength and liquidity. Badulescu et al. (2020)

concluded that profit, return on investment, turnover, or customer portfolio, improvements in product quality can be considered as standard indicators to measure business performance. Situm (2013) developed business failure prediction models based on multivariate linear discriminant analysis and logistic regression with the use of four selected financial indicators (equity ratio, EBIT (Earnings Before Interest and Taxes)/total assets, operating cash flow/total liabilities and percentage sales development), which led to a classification of companies in three categories (healthy, crisis-resistant and insolvency endangered). Cabinova et al. (2018) selected indicators such as EVA (Economic value-added), RONA (Return on net assets), Creditworthy Model, Simplex Linear Programming Method and examined the financial performance of the Slovakians' spa companies, during the years 2013–2017, aiming to design an Enterprise Performance Model. Song et al. (2018) chose 27 financial indicators to predict business performance with the help of traditional machine learning and the Fuzzy Chance Constrained Least Squares Twin Support Vector Machine (FCCLSTSVM) technique (Han & Cao, 2017). The selected financial indicators reflected the companies' solvency, profitability, operational capabilities, business development capacity, structural soundness, and capital expansion capacity. Kiselakova et al. (2018) and Horváthová et al. (2015) used the Creditworthy Model (CWM), one of the modern models of enterprise performance evaluation, considered to be one of the most suitable methods for comparison business performance of enterprises. CWM has its performance portfolio, which consists of financial performance indicators and enterprise success indicators (Horváthová et al., 2015).

Predictions of business indicators, mostly forecasting corporate bankruptcy, represented a center of major interest in corporate finance and accounting research since the 1960s (Camska & Klecka, 2020). Back then, financial prediction models described a particular economic reality (Camska & Klecka, 2020), and were based on multivariate discriminant analysis and logistic regression (Balcaen & Ooghe, 2006). In the last decades with the development of artificial intelligence, more and more studies have begun to use machine learning to predict financial indicators, also to predict the business performance of companies (Hu et al., 1999; Ahn et al., 2000; Huang et al., 2005; Min & Lee, 2005; West et al., 2005; Estrella & Mishkin, 1996; Hsu et al., 2009; Ribeiro & Lopes, 2011; Lin et al., 2011; Li & Sun, 2013; Shen et al., 2015). The neural network concept was firstly designed in biology and psychology, and then it was imported and used with notable results in medicine, business, and economics, and also in other research areas (Vochozka & Sheng, 2016; Horak et al., 2020). Neural networks, a sub-domain of machine learning, based on practical data and a brief description, build algorithms that allow solving problems and making predictions. This is achieved (Bishop, 2006; Marginean et al., 2019) by learning the characteristics and testing the algorithms on the sample data to allow the introduction of static equilibrium with a new set of input data. It is worth mentioning, Vochozka and Machova (2018) observed that artificial neural networks allow the construction of strong models for various economic issues.

Björklund and Uhlin (2017) highlighted that a neural network model that predicts financial time-series requires a well-founded rational process of choosing the used parameters. Thus, several works used numerical and also narrative data, to build forecasting business performance models (Qiu et al., 2014). Quarterly reports and financial ratios were processed

and classified using self-organizing maps, by Magnusson et al. (2005) and found that the changes in narrative reporting tend to predict changes in financial performance. Li et al. (2010) used the decision tree (DT) model for financial ratio classification and predicted the short-term business failure of Chinese listed companies. Based on back-propagation neural networks and chance-constrained least squares twin support vector machine to process uncertain data, Song et al. (2018) used financial indicators to predict business performance. They found that business performance predictions are related to the industries. Lee et al. (2017) proposed a deep neural network-based performance prediction model using financial and patent indicators.

There are some key arguments as we found in Gujarati (2002), Mulford and Comiskey (2002), and Huang et al. (2008) which support hybrid business prediction analysis, models based on machine learning techniques: the use of a large number of parameters as inputs, the selection of various financial indicators, and the choice of an efficient and accurate method to diagnose bankruptcy risk and predict company performance. Huang et al. (2008) proposed a hybrid financial analysis model based on a back-propagation neural network that showed a high prediction accuracy. The back-propagation algorithm and neural networks for financial performance prediction were also investigated by Lam (2004). The experimental results (Lam, 2004) indicated that neural networks using financial data of one year or more years exceed the minimum reference value, but not the maximum reference value. Based on six financial ratios, Elsadek et al. (2017) developed a neuro-fuzzy model to evaluate the financial performance of residential construction companies. Fuzzy clustering was performed to group the data and construct the performance index, and the neural networks model was designed to evaluate and predict the performance. Kadhim and Erzaij (2020) used principal component analysis (PCA) on road works contract projects and train artificial networks (ANN) model to construct criteria-performance mapping. Their results proved the nonlinear correlation between financial performance and constructors' capabilities. Maestri et al. (2019) proved that the neural networks model of financial performance forecast of the companies listed on the Brazil market obtained better accuracy than the models developed for non-listed companies.

To develop an accurate model of financial performance prediction, based on a composite indicator, this study resorted to principal component analysis (PCA). This method dates from the works of Pearson (1901) and Hotelling (1933) and has been analyzed over several decades (Cattell, 1966; Jolliffe, 2002; Jolliffe & Cadima, 2016). The objectives of PCA are to (Abdi & Williams, 2010) select and extract the important information from a relatively large database further, the attribute space is reduced from a larger number of variables to a smaller number of factors; select a smaller number of variables from a larger set, so that the original variables have the highest correlations with the main component.

2. Data collection and descriptive statistics

The study aimed to predict the financial performance of listed companies with the help of neural networks using eight financial indicators grouped into two categories, accounting, traditional indicators, and value-added indicators. They were calculated manually, for the

years 2011–2018, using the information presented in the annual financial statements of the selected companies. The sample consists of Romanian listed companies who are required to apply International Financial Reporting Standards (IFRS), in their accounting, starting with the year 2012, according to the provisions of Order no. 881/2012. Since as of January 1, 2013, IFRSs are used as the basis of accounting for listed companies, the Ministry of Finance issued Order no. 1286/2012, which contains regulations for preparing, auditing, submission, and publication of financial statements; specific recording rules for transactions and the charter of accounts in compliance with the IFRSs, as well as the rules for transposing the accounts and presentation requirements.

The sample comprises 57 companies listed on the Bucharest Stock Exchange (BSE). For the calculation of the selected indicators, the data were collected both by accessing the company's web page and the information published on the BSE website. Thus, data was collected mainly from the statement of the financial position, profit and loss account, statement of comprehensive income, statement of cash flows, and explanatory notes, for the years 2011–2018. The year 2011 was chosen, for the first year of information collection and processing, as the balance of accounts drawn up on December 31, 2012, restated based on IFRSs, is the accounting document on which the individual financial statements were drawn up at the end of the financial year 2012, IFRS compliant. To ensure comparability of information from one reporting year to another, and to respect the principle of consistency and continuity of activity, we started in our study collecting information with the year 2011. The selected companies were grouped into eight industries. Thus, 39 companies were analyzed from the manufacturing industry, 4 companies from transport and storage and also, 4 companies from the wholesale and retail trade industry, 3 companies representing hotels and restaurants, 2 companies from extractive, energy and constructions industries, and a company from professional scientific and technical activities industry.

Eight financial indicators were selected to determine the financial performance of sampled companies. The indicators calculated for the present study were grouped into value-added indicators: EVA (Economic value-added), MVA (Market value-added), CFROI (Cash flow return on investment) and CVA (Cash value-added), and classic accounting indicators: (Earnings per share), ROA (Return on assets), ROE (Return on equity) and SOL (Solvency). These indicators were calculated for each company in the sample and each year if the necessary information was disclosed and the company remained listed on the BSE. For the EVA, MVA, CFROI, and CVA indicators, those calculation formulas accepted by the accounting literature, were chosen, that allowed the determination of the indicator based on information found in the financial statements of the companies.

In Figure 1, we presented the framework of our empirical study conducted to predict financial performance through the composite index and by recourse to neural networks. The used financial indicators descriptive statistics are summarized in Table 1.

Based on the financial indicators, we aimed to build a composite performance measurement indicator, according to which the analyzed companies can be grouped into companies that performed better from one year to the next or on the contrary, and also followed the achievement of the financial performance prediction. These aspects are presented in the following sections.
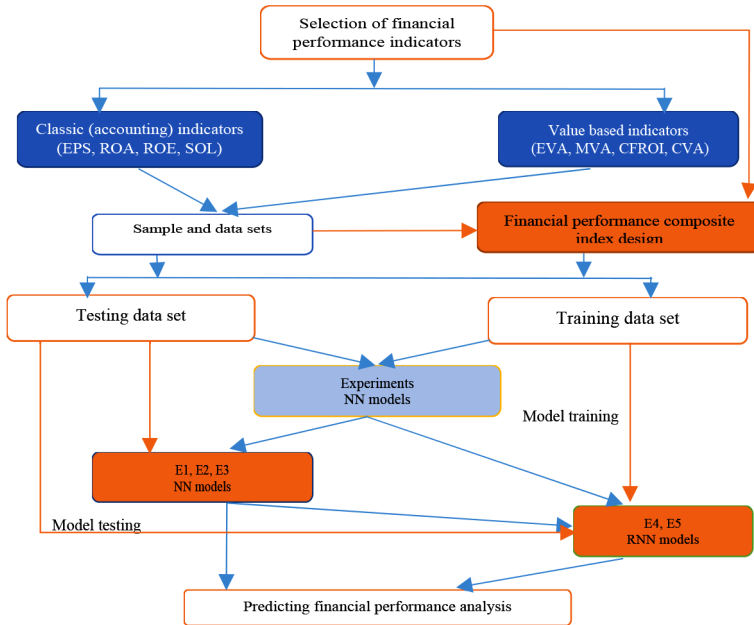
Figure 1. The framework of the empirical experiments of financial performance composite index prediction

Table 1. Descriptive statistics (source: authors' calculation)

	EVA	MVA	CFROI	CVA	EPS	ROA	ROE	SOL
	Value-added indicators				Classic accounting indicators			
Mean	−9 654 853.8	−806 656 502.8	0.02	−37 975 205.7	0.31	0.02	0.08	5.61
Median	20 457.12	−109 049 353.2	0.03	−195 155.81	0.04	0.03	0.06	3.15
Minimum	−3 876 998 017	−26 426 073 015	−1.77	−2 448 487 897	−281.6	−1.47	−12.01	0.41
Maximum	320 670 806	2 700 421 856	1.63	239 532 259.2	50.5	0.29	10.13	192.2
Standard Deviation	188 641 413	3 099 105 272	0.135	193 700 972.5	14.6	0.11	0.82	11.38

3. Financial performance composite index design using PCA

To build a performance measurement indicator, we will use PCA. This technique calculates new variables obtained as linear combinations of the original variables. These new variables are called principal components. The first principal component (PC) recovers the greatest variation from the original variables. The second PC is not correlated with the first PC and represents most of the remaining variations possible, and so on. The method will have as particularities the fact that it applies to a panel dataset.

Given that there are significant differences between the units of measurement of the eight financial indicators analyzed, these data must be standardized. From the standardization methods presented by Freudenberg (2003) and OECD (2008), standardization transforms indicators on a common scale, with the mean 0 and the standard deviation 1. In the analysis of the principal components, different criteria are used to choose the optimal number of components. The most important criteria are Kaiser's criterion, Evrard's criterion, Benzecri's criterion (Saporta & Stefanescu, 1996). After identifying the companies' performance factors, the next step consists in to group these determinants into a composite index. The index measures the performance of companies from one year to another using a linear scale. Because the value of the composite index can be both positive and negative, it is difficult to interpret. For a better interpretation of the results and also to realize the forecast, the index will be transformed using the rank of percentiles so that this index will take values between 0 and 100. The evaluation of the performances of the sample companies for the period 2011–2018 was based on the construction of a composite index based on panel data, identifying the determining factors in the evaluation of the performance of the analyzed companies using the analysis in principal components suitable to the panel data. The main purpose of this section is to establish the principal factors in assessing the performance of the sample companies using the Principal Component Analysis technique for panel data. This composite index will be determined using EViews 9 software (IHS Global Inc, 2017).

Table 2. Eigenvalues of the principal components (source: authors' calculation using EViews 9)

PCA: Eigenvalues (Sample: 2011–2018)				
Number	Value	Difference	Proportion (%)	Cumulative proportion (%)
1	1.893153	0.565034	23.66%	23.66%
2	1.328119	0.073278	16.60%	40.27%
3	1.254840	0.218729	15.69%	55.95%
4	1.036111	0.088672	12.95%	68.90%

Table 2 contains the eigenvalues for the first four principal components and the eigenvectors related to each of the principal eigenvalues. Based on Kaiser's criterion (Kaiser, 1960), only the components with the eigenvalues greater than 1 can be maintained. Thus, in our analysis, we will keep only the first four PC ($\lambda_1 = 1.893$, $\lambda_2 = 1.328$, $\lambda_3 = 1.254$ and $\lambda_4 = 1.036$).

As regards the covering proportion, those four principal components preserve roughly 69% of the total variance. Therefore, if we want to reduce the dimensionality, our analysis indicates that we can reach half the basic dimensionality problem from 8 to 4 while retaining almost 70% of the original information.

The results presented in Table 3, summarizes the eigenvectors associated with each of the principal eigenvalues. If the eigenvalues show how much general information is extracted in each main component, the eigenvectors show how much weight each variable has in each component. Thus, the relative importance of any variable in a PC is the proportion of the eigenvector length assigned to that variable.

Table 3. Eigenvectors of the principal components (source: authors' calculation using EViews 9)

	Principal Components Analysis (Sample: 2011–2018)				
Variable	PC1	PC2	PC3	PC4	PC5
	PCA coefficient				
CFROI	−0.08 (0.01)	0.18 (0.04)	0.07 (0.01)	0.88 (0.79)	−0.20 (0.04)
CVA	0.61 (0.38)	0.26 (0.07)	−0.11 (0.01)	0.01 (0.0002)	−6.09E–04 (3.71E–07)
EPS	−0.29 (0.09)	0.45 (0.21)	0.42 (0.18)	0.13 (0.02)	0.18 (0.03)
EVA	0.37 (0.14)	−0.17 (0.03)	0.54 (0.30)	−0.05 (0.002)	0.03 (0.001)
MVA	0.56 (0.31)	0.41 (0.17)	−0.01 (0.0001)	0.04 (0.002)	0.13 (0.02)
ROE	0.04 (0.002)	−0.31 (0.10)	−0.15 (0.03)	0.29 (0.08)	0.88 (0.79)
ROA	−0.25 (0.06)	0.49 (0.24)	0.25 (0.06)	−0.31 (0.10)	0.34 (0.12)
SOL	−0.10 (0.01)	0.38 (0.15)	−0.64 (0.41)	−0.04 (0.001)	0.04 (0.001)

Note: In parenthesis – the proportion of the eigenvector length assigned to that variable.

In the case of the first eigenvector, the CVA and MVA represents 0.38%, respectively 0.31% of the total component, while the other six accounts each less than 0.15% of the total component. In the second principal component, ROA and EPS represents 0.24%, respectively 0.21% of the total component, SOL and EVA, represents 0.41%, respectively 0.30% of the third total component, while CFROI represents 0.79% of the fourth total component and ROE, 0.79% of the fifth total component.

According to Figure 2, we can say that two variables, CVA and MVA are strongly correlated with the first main component, while the other two, ROA and EPS are strongly correlated with the second main component. In fact, by analyzing the vector lengths, we can also observe that CVA and MVA are approximately as dominant in the first component, while EPS and ROA are significantly more dominant than any of the other variables, in the second component. The angle between the vectors of a loading plot is related to the correlation
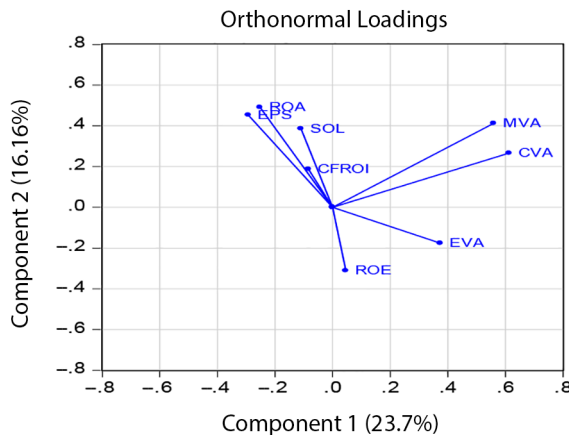

Figure 2. Orthonormal Loadings (source: authors' calculation using Eviews 9)

between the original variables to which the loading vectors are associated. Figure 2 shows that CVA, MVA, EVA, and ROE are negatively correlated with SOL, ROA, EPS, and CFROI. Also, CVA and MVA are nearly uncorrelated with ROE since they form an angle greater than 90 degrees. Also, in the analysis of main components to facilitate the interpretation of these components, a procedure of axis rotation is used. This technique aims to obtain a correlation coefficient as low as possible on one or two main components. For numerical data, one of the most popular axis rotation techniques is the Varimax technique (Kaiser, 1958).

Table 4. Factor matrix (source: authors' calculation using EViews 9)

Rotation Method: Orthogonal Varimax Kaiser row weighting (Convergence achieved after 7 iterations)			
Variable	Factor 1	Factor 2	Factor 3	Factor 4
CVA	0.759307	−0.141593	0.049939	−0.070707
MVA	0.754544	0.043837	0.058102	0.014156
ROA	−0.067743	0.446975	−0.080584	0.032063
EPS	−0.118219	0.476106	(0.020358	0.225404
EVA	0.220118	0.050974	0.492266	−0.059985
SOL	0.062694	0.051041	−0.476778	0.012628
CFROI	−0.008721	0.043310	−0.02742	0.284041
ROE	−0.026831	−0.181419	0.017295	0.005693

For the proper interpretation of the principal components, we calculated the correlation coefficients among the initial variables and the four principal components. Analyzing the matrix factor presented in Table 4, it can be seen that: the first PC is positive, correlated with CVA (0.759) and MVA (0.754) variables; the second principal component take positive information from ROA (0.446), respectively from EPS (0.476) and negative information from ROE (0.18); the third principal component is positive correlated with EVA (0.492) and negatively correlated with SOL (0.476); the fourth one is correlated with CFROI (0.284). In the last stage of the composite index construction, we determined the weights of the rotated principal component matrix, considering that each principal component has a share equal to its proportion of variance recovered from the total variation explained by all factors (*PC*1 – 23.66%, *PC*2 – 16.6%, *PC*3 – 15.69% and *PC*4 – 12.95%). Thus, the financial performance index (FPI) of companies is determined as follows:

$$FPI = \frac{23.66}{68.90}PC1 + \frac{16.60}{68.90}PC2 + \frac{15.69}{68.90}PC3 + \frac{12.95}{68.90}PC4.$$

The final amount granted to each observation for each company is rescaled utilizing the percentage rank. Thus, the composite index of financial performance will indicate how a company has evolved in a year compared to the previous year or with another company in the same year or different years. The index will be between 0 (lowest performance) and 100 (highest performance).

4. Description of the prediction model using neural networks

A basic model of an artificial neural network comprises three elements: input, hidden and output layers and each layer has a set of neurons, which allows the connection with the neurons of the next layer (Hu et al., 2018). A neural network model is based on the mathematical formula (Hu et al., 2018):

$$O_k = u_2 \left[\sum_{j=1}^{K} W_j^k u_1 \left(\sum_{i=1}^{R} W_i^j x_i + W_o^j \right) + W_o^k \right],$$

where: x_i is the input, with i = 1, 2, ..., R, O_k is the output, with k = 1, 2, ..., K, u_1 is the non-linear activation function for the hidden layer, u_2 is the linear activation function for the output layer. R is the number of inputs, K is the number of hidden neurons, W_o^j and W_o^k are thresholds of the jth neuron in the hidden layer, and the kth neuron in the output layer. W_i^j is the weight associated with the connection between the ith input and the jth hidden neuron, and W_j^k is the weight associated with the connection between the jth hidden neuron and the kth output neurons. Recurrent neural networks (RNN) are the most commonly used types of neural networks for sequence prediction issues (Hewamalage et al., 2019). Various types of RNN architectures can be found in the literature. In the present study in E4, we performed Sequence to Vector (S2V) and in E5, we used RNN Sequence to Sequence (S2S) model, inspired by Sutskever et al. (2014).

The dataset includes observations for eight years. To predict the financial performance index for a certain year, observations from previous years are used. The simplest idea would be to predict for the next year based only on what happens this year. But, if not only the values but also the evolution of the parameters influences the prediction, then the prediction should consider observations from more than the current year. Therefore, we were interested in obtaining the neural network model that can predict with the best accuracy, the evolution of the financial performance composite index. The model will consider only the variables that will have a significant influence on the composite index. The neural network with the best performance in training, testing, and cross-validation, of the data set and minimal error, but also an accurate interpretation, will be selected (Vochozka & Machova, 2018). In this regard, we performed 5 experiments – 2 classifications and 3 regressions, with feed-forward neural networks (E1, E2, E3), respectively recurrent neural networks (E4, E5). The networks were built and trained with Tensorflow2 and Python 3.6.

E1. Classify observations of one year in two classes: 1 if the index increases in the next year and 0 if the index decreases in the next year. There are 196 cases where the index decreased in the next year and 185 cases of increase (out of a total of 381). The first experiment E1 involved training a relatively small feed-forward neural network for classification in these two classes. Since there are cases where the financial performance index increased or decreased with a very small amount, we considered also a split in 3 classes: increased with more than a threshold t ($\Delta index = index_{year} - index_{year-1} > t$), almost the same $-t < \Delta index < t$, decreased with more than t. Therefore, in the experiment E2, a similar network was trained with three classes, for t = 0.0015. With this value for t, there are 123 cases in class 0 – decrease, 140 in class 1 – almost the same value for the index, respectively 118 in class 2 – increase.

Table 5. Number of samples in E1 and E2 (source: authors' calculation)

Increase (class 1)	Decreases (class 0)	Total	Increase more than t	Almost the same	Decrease more than t	Increase (class 1)
185	196	381	118	140	123	185
157	166	323	96	121	106	157

E2. Classify observations of two successive years in two classes (increase/decrease), respectively 3 classes as in E1.
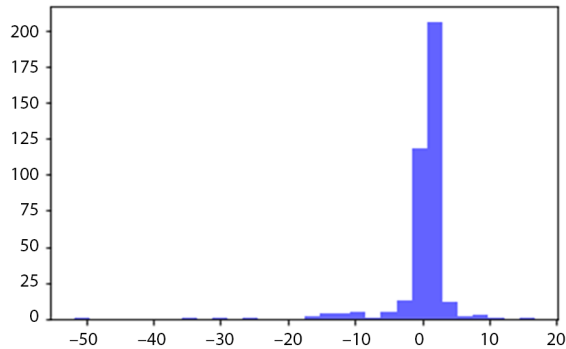

Figure 3. Histograms of values for FP index in years 2012–2018 (without 2011)

E3. Perform a regression for the financial performance index value, meaning predict the value for the next year based on observations for the current year. Since the values are very small, we predict the index*100. Consequently, the range is (–51.83,16.72).

Table 6. NN structure for E1 and E2/Regression NN for 2 years E1, E2 (source: authors' calculation)

Neural networks structure for E1 and E2			Regression neural networks for 2 years E1, E2		
Layer (type)	Output Shape	Param #	Layer (type)	Output Shape	Param #
dense_37	(None, 32)	688	dense_25	(None, 32)	688
dropout_19	(None, 32)	0	dropout_12	(None, 32)	0
dense_38	(None, 8)	264	dense_26	(None, 16)	528
dropout_20	(None, 8)	0	dropout_27	(None, 1)	17
dense_39	(None, 3)	27	Total params: 1153/Trainable params: 1153/ Non-trainable params: 0		
Total params: 899/Trainable params: 899/ Non-trainable params: 0					

The network trained in E1 and E2 has 5 layers (Table 6): a Dense with 32 neurons, a Dropout with probability = 0.4, another Dense with eight neurons together with another Dropout, and lastly a softmax layer. As it can be observed in Table 5, the number of samples is very small, which affects the quality of the trained network. E4 and E5 perform recurrent neural networks as described in section six of the current study.

5. Data analysis and discussion of results

To alleviate this, we repeated E1 and E2 on the different splitting of the datasets (similar to cross-validation) and several times on the same split in train and test. On average, E1 reaches at most accuracy 0.63 on train and 0.61 on the test set, while in E2 the values are smaller.
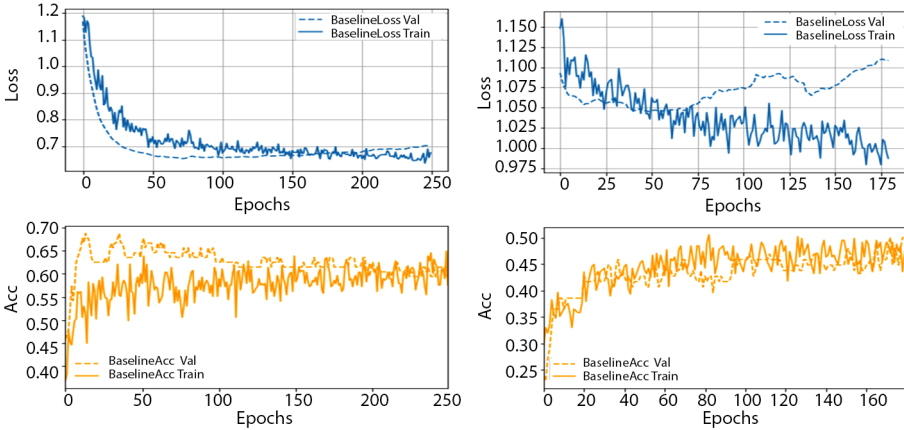

Figure 4. Classification: Left – exp E1a), right – exp E2a), classification in classes with observations from one year

In Figure 4 it can be observed that overfitting appears in E1 around epoch 180 when the loss on validation starts to increase, while on train set it continues to decrease. The addition of the third class in E2 does not improve the accuracy, on average the values of accuracy are below 0.5; a possible reason is a wrong value for the threshold. The current value for threshold was set such that the resulting dataset is balanced (similar number of samples in all three classes). As it can be observed from the histogram in Figure 3, the majority of values for 100 × index are around 0, with a small number of values at the margins of the interval.

As expected, the model trained in E3 reaches MSE (mean squared error) significantly worse than MAE (mean absolute error) (see Figure 3). Consequently, for the experiments with RNN, we tried to change the distribution of values, so instead of 100*index, we used $sign(index) \times \sqrt{index \vee}$ which shrinks the values greater than 1 and increases the values between (−1, 1).

Further on, all three experiments (**E1, E2, E3b**)) were repeated with the same output but with observations from two years instead of just one year as an input. For regression (E3), the values of MAE and MSE for train and test set improved significantly (see Figure 5 – for metrics values, we mention first the value obtained on the train followed by the one obtained on test; the values are the average of the best-obtained values in 10 repeated experiments).

In Figure 6, it can be observed that MAE improved from an average of 0.87/1.37 to an average of 0.27/0.18. More important, MSE improved from 2.71/12 to 0.34/0.41. The improvement of both metrics on both train and test sets can support the conclusion that the value for the financial performance index in the next year depends not only on the values for the
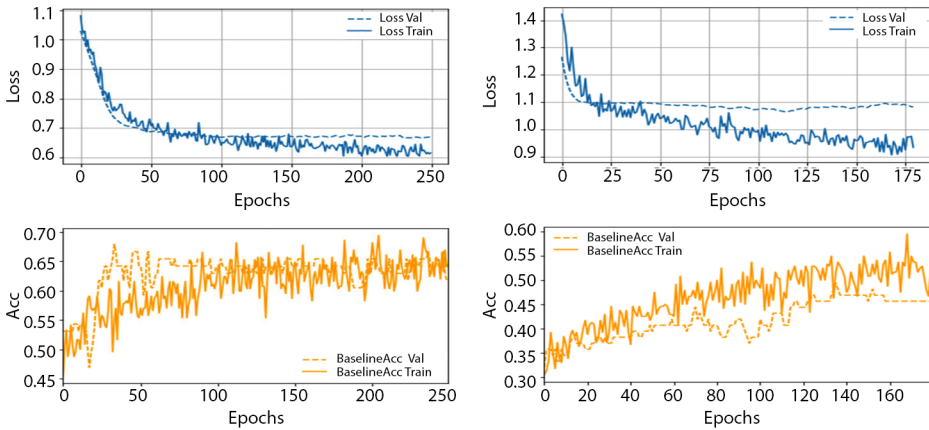
Figure 5. E2b) and E3b), classification in two, respectively 3 classes with observations from 2 years
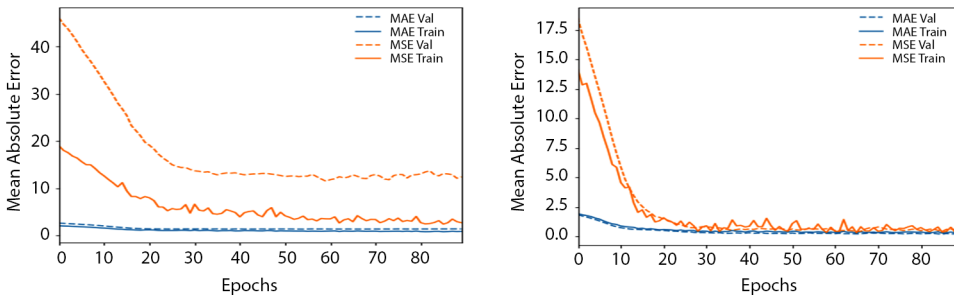

Figure 6. Experiment E3. Regression with observations from one year
(average MAE = 0.87/1.37, MSE = 2.71/12) E3a) left; observations from two years
(average MAE = 0.27/0.18, MSE = 0.34/0.41) – E3b) right

current year but also on the values of the previous year. The fact that for E3 a), in the majority of the experiments, the values for MSE on validation are much higher than the values on the train set must be correlated with the meaning of MSE (i.e. the average of the squares of the errors) and with the histogram of the index: the trained models do large errors (especially on new data) which are emphasized through squaring. This behavior which is a sign of a bad prediction model is not present anymore on E3b), meaning that the observations from more than one year are necessary to predict the value of the performance index. When it comes to classification, E1 and E2 did not change significantly when two years were considered, the only stable difference is that in E1, the overfitting – identified as a greater loss on test set compared to test set – appears sooner at almost the same value of loss and accuracy (around epochs 100 in E1b compared to epochs 180 in E1a)), meaning that the model learns sooner when it gets observations from two years. The learning of three classes is still worse than learning of two classes (E2b compared to E2a). From version b) of the experiments E1, E2, and E3 we could conclude that the financial performance index is clearly related to the evolution of the other financial indicators and not only values from one year, therefore we continue with experiments better suited for training on sequences.

Recurrent neural networks

Since version b) of E1, E2, and E3 proved more stable than learning from just one year, in experiments **E4** and **E5** we trained recurrent networks to forecast a multivariate time series. In E4 the model sequence2vector was used, while sequence2sequence in E5, and both for regression. The structure of the networks can be observed in Table 7.

Table 7. The structure of the networks in E4 and E5 (source: authors' calculation)

RNN structure for E4 and E5			Regression RNN E4, E5		
Layer (type)	Output Shape	Param #	Layer (type)	Output Shape	Param #
lstm_2	(None, 7, 24)	3264	simple_rnn	(None, 7, 24)	816
dropout_23	(None, 7, 24)	0	dropout_9	(None, 7, 24)	0
lstm_3	(None, 7, 12)	1776	simple_rnn_1	(None, 12)	444
dropout_24	(None, 7, 12)	0	dense_21	(None, 1)	13
time_distributed_1	(None, 7, 1)	13	Total params: 1273/Trainable params: 1273/ Non-trainable params: 0		
Total params: 5053/Trainable params: 5053/ Non-trainable params: 0					

In the data set, we kept only companies with all indicators known for all years, meaning 48-time sequences of 8+1 features. The loss function is MSE. First, in E4 a) we considered MSE applied only for the prediction of the index for the last year 2018. So, the network learns to predict the index for 2018 and it computes error based only on this prediction. Since it is a recurrent network, the input for a one-time step consists of the features for one year and the output of the network is passed for prediction of the next time step. In the sequence2vector approach, only the last output is used for computing the error, while in sequence2sequence all the outputs are considered, meaning that the errors consider all the predictions for the index from 2012 to 2018.

It can be observed that the best values for MAE and MSE on the train are comparable in E4 (see, Figure 7) and E5 (see, Figure 8). But in E5 the differences between MSE and
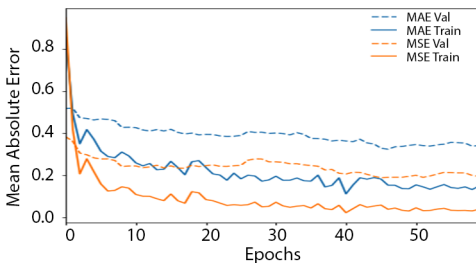

Figure 7. E4. Simple RNN for sequences of length 7 (average MSE 0.03/0.21, MAE 0.13/0.33) with the error considering the predictions for the index in 2018
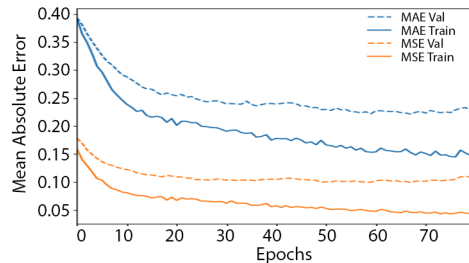
Figure 8. E5. LSTM (Long Short-Term Memory) for sequence of length 7 with error considering all predictions for the index during 2012–2018 (average MSE 0.04/0.09, MAE 0.15/0.19)

MAE on train and test set are smaller, meaning that the models can predict better new data in E5.

This is explained by the fact that the model learns by reducing an error which considers more real data for index (2012–2018) instead of just 2018 in E4. Below, (see, Figure 9) we present some examples of financial performance index predictions given by models in E5 and E4 on data that were not included in the training set.

As we can see from Figure 9, the prediction model from E5, based on sequence 2 sequence and regression, considering all predictions for the composite index during 2012–2018, presents the best prediction.
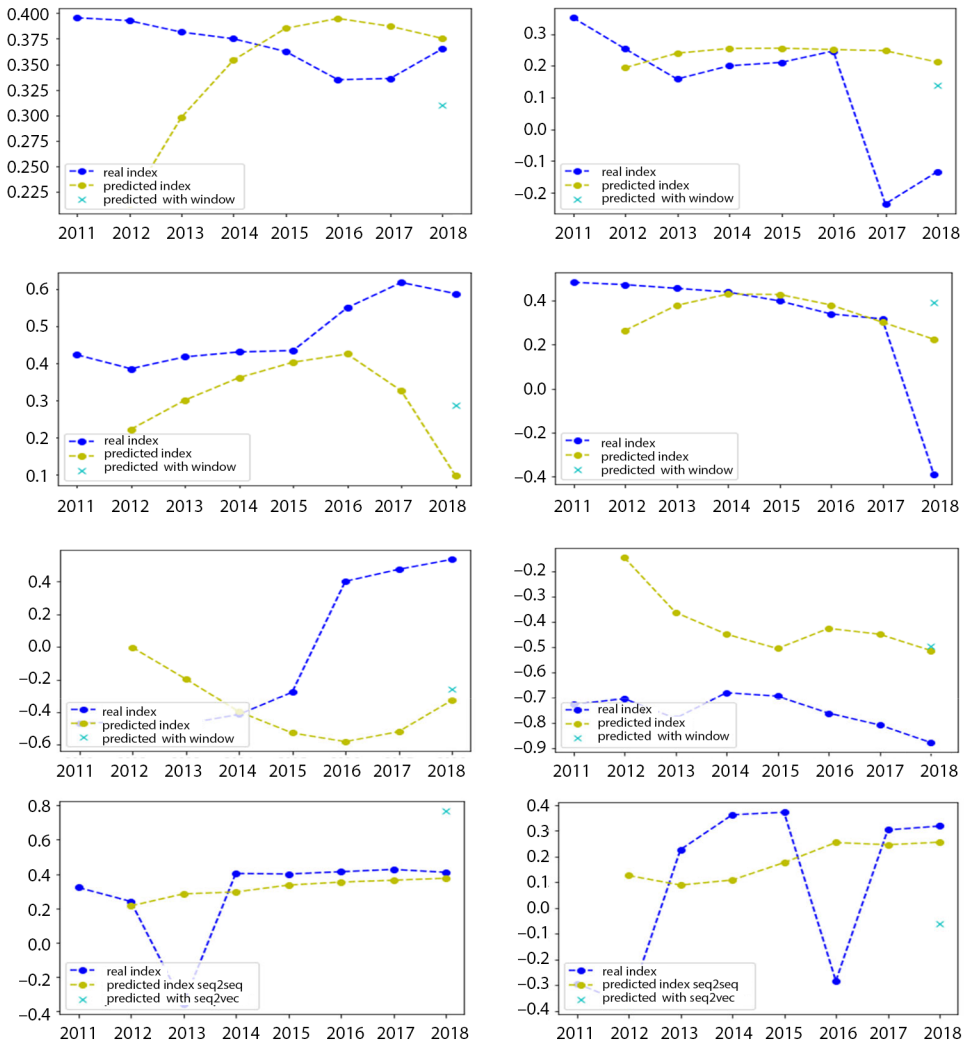
Figure 9. Examples of financial performance index predictions (models E5 and E4)
on data not included in the training set

Conclusions

This study presented a neural network financial performance prediction model for Romanian listed companies. Business performance prediction is based on a composite financial index. In this regard, starting from eight financial indicators grouped into two categories, traditional accounting indicators, and value-based indicators, a performance index was built, based on panel data. The research work was conducted in two steps, using 456 financial data about 57 Romanian listed companies. In the first step, using PCA data was classified, followed by the design of the performance index, and in the second step with the use of neural networks, a performance prediction model was developed based on the composite index and the selected financial indicators. The composite index was built to aggregate financial information on the company's performance and to facilitate the prediction of its evolution using neural networks. A composite indicator can provide a more real and relevant image of financial performance, being composed of both components of classical indicators and value-added indicators. Thus, the developed model offered a good prediction and satisfying results and can be used to evaluate and predict the financial performance of listed companies. The study contributes to the development of the literature by modeling prediction of financial performance based on the composite index, not just on the prediction of certain individual indicators.

To achieve the prediction model using neural networks, the procedure was as follows: firstly, to predict the financial performance index for a certain year, observations from previous years were used, and secondly, the study presents 3 experiments. It can be observed that version b), with observations from two years, of the experiments E1, E2, and E3 show a better predictive behavior than version a), with observations from one year, of the same experiments. So far, we have concluded that the observations from more than one year are necessary to predict the value of the financial performance index. Thus, it can be highlighted that the performance index prediction as a composite indicator is related to the evolution of the financial indicators and not only their values from one year but previous years, also. Therefore, the study continued with experiments that are more suitable for training on sequences. In experiments, E4 and E5 recurrent networks were trained. In E4 the model sequence 2 vector was used, while sequence 2 sequence in E5, and both for regression. In E5 the differences between MSE and MAE on train and test set are smaller. So, the models can predict better new data in E5. Findings from the performed experiments led us to the conclusion that recurrent neural networks model predicted better financial performance composite index when taken into consideration more real data for the index (2012–2018) instead of just 2018. Therefore, neural network models designed for the prediction of business performance can be considered useful tools for managers. Through these management tools, it is possible to build future strategies of performance optimization based on the experiences of previous years and analyzed through the lens of the current financial situation.

The limits of the financial performance prediction model can be found in a small sample of companies and the data collected from 2011 to 2018. Future research will focus on designing other business performance prediction models and with higher accuracy of the prediction, based on input data that includes not only financial variables but non-financial information, also.

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Author contributions

VB, DNP and RS conceived the study, DNP collected the data, VB and RS designed the research methodology and developed the first analysis of the data. DSP, VB and RS were responsible for data interpretation and discussion of results. VB and RS conceived the conclusions and wrote the first draft of the study. DSP and DNP wrote the second draft of the article. All authors have read and agreed to the published version of the manuscript.

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