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An Artificial Neural Network Growth Analysis in Construction Businesses

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Abstract – This research paper explores the firms' growths analysis through Artificial Neural Networks, explicitly using the Multilayer Perceptron (MLP) Analysis in a panel of construction businesses operating in the country. The construction businesses data used are classified into Organizational characteristics (5 patterns) and Financial indicators (18 patterns). They refer to Liquidity (5), Operational Efficiency (4), Leverage (4), and Growth (5) patterns. Thus, 85 construction business data from 2020-2021 have been collected, but only 31 businesses are considered valid for Multilayer Perceptron analysis training purposes. The first research step before building the multilayer perceptron neural network is the implementation of the Receiver Operating Characteristics (ROC curve) Analysis at a 95% confidence level, considering as a dependent variable the firms' age [in start-up (0); growth (1) and those in the maturity phase (2)]. Then, based on ROC analysis results, a multilayer perceptron network with 10 input layers patterns, 10 customers' patterns factors, and one covariate is implemented. The number of hidden layers is 1, and the number of units in hidden layers is 20. The activation function used is Hyperbolic tangent. Thus, the empirical findings of the research provide construction businesses and line ministries with valuable insights on boosting their growth.

Keywords – Multilayer Perceptron Analysis, ROC Analysis, Business Organizational Characteristics, Construction Businesses, Financial Patterns

I. Introduction

This document represents a template for ICPIS. It can be downloaded from the conference website, and used as a reference in the typesetting of the final paper to be included in the conference proceedings. Construction has become one of Albania's main sectors that support economic growth, driven by the increase in residential projects, the continuation of post-earthquake reconstruction works, and public investments mainly focused on road construction.

According to 2022 statistics, since 2014, the sector has returned to the expanding cycle, and in 2022 it exceeded even the highest construction level reached in 2008 [1]. The weight of the construction sector to the total GDP increased by 0.6 percentage points to 9.6%. The sector grew double-digit in the first three quarters (up to 40% in the second quarter) during 2022. Most of the construction companies reported a significant increase in income, especially those involved in the residential sector.

The annual turnover of construction companies (or subcontractors) and those related to them increased by 32% annually during 2022. Compared with last year's data, the increase is 11.4% after the contraction of 7% in 2019 (due to the earthquake circumstances). However, it is worth highlighting that construction businesses report large fluctuations in their activity, depending on the engineering projects they are involved in or from the apartment sales cycle.

Against the shrinking population trend and the slow growth of official income, the residential construction sector is following the activity, especially in the country's capital, Tirana.

During the year 2021, the area of building permits reached a record level in the last decade [2]. However, the construction trend is expected to continue because only in the first quarter of 2022, the area of permits was about 800 thousand square meters, half of the entire year 2021. Nevertheless, after a long marathon influence from real estate price increase during 2022, the market has reached the finish line in 2023 because buyers are suffering from the increase in loan interest, in close reference to a restrictive monetary policy implemented by the Central Bank.

Thus, results are important to analyze the factors influencing construction businesses' growth. For this purpose, neural networks, fuzzy sets, expert systems, gnostic theory of indefinite data or genetic algorithms, etc., are among the non-static higher methods of business growth [3], to name a few. The researchers argue that artificial neural network evaluation includes even the competition in the environment in evaluating a business's growth. This is important to identify, understand, adopt best practices, and capture the opportunity to establish standards against which processes, services, and products can be compared and improved [4]. Nowadays, the neural model results are most preferred because technological advances push construction businesses to automate their growth analysis. In the Albanian literature on the matter, there needs to be more in using these models for business growth analysis purposes.

Therefore, this paper aims to analyze the ability of the artificial neural networks, through the Multilayer Perceptron Analysis, to perform business growth analysis in a panel of Albanian businesses operating in the construction sector. The empirical findings of the research provide businesses and line ministries with some valuable insights for further developments in the sector.

II. Literature Review

The essential resource in gaining competitive advantage in today's construction business environment constitutes a complex approach featured with financial techniques and the well-known characteristics of the construction industry (i.e., project-based, knowledge-intensive, demand-driven, etc) and, at the same time, presents new challenges to construction firms [5].

In order to create a sustainable competitive advantage, it means that a firm should outperform its rivals on some criteria, such as :
(i) financial context—profitability and return on investment ([6]; [7]):
(ii) process management—continuous improvement, streamlined internal processes, innovative construction methods and contracting services, and sustainable technological changes [8];
(iii) market development—growth in identifying opportunities for new construction projects and markets [9];

Alternatively, (iv) customer/client portfolio—increasing client satisfaction and gaining customer trust [10]. Shreds of evidence on the matter have shown that sustainable business growth occurs in different stages measured by life-cycle periods or the firm's age (FA) [11]. The stages are : (1) commercialization related to business start-up, (2) growth, and (3) maturity. This leads to insight into the knowledge management concept and how it can be measured and used for improvement in construction firms.

Therefore, worth also highlighting the importance of social knowledge practices in construction business growth. Social knowledge practices refer to the sum of the actual and potential resources that derive from social entities' relationships and interactions (i.e., individuals, departments, and firms) [12].

These practices can be decomposed into two main components : (a) organizational culture and (b) organizational structure [13]. Meanwhile, the organizational culture includes a set of values, norms, beliefs, expectations, and assumptions widely shared [14].

Thus, the business growth analysis represents a fair and accurate evaluation of the company's operation, including even complex statistics related to their operative research principles [3].

The last study confirms that nowadays, a set of tools are used for complex business growth analysis. They are able to predict the financial health of the enterprise, including bankruptcy, creditworthiness, and bankruptcy models.

However, dealing with business growth analysis in the construction sector, the researchers report that they are predominantly focused on project performance in close reference to time, cost, and quality ([15];[16];[17]. However, the current practice is also shifting towards the organizational level. Due to these circumstances, the construction business frameworks have been reviewed and critically evaluated ([18]; [19]). Furthermore, the issue of artificial neural networks as a relatively young branch has recently been associated with the business growth analysis logic [20]. Therefore new types of artificial neural networks are still emerging, together with the massive development of information technologies and computer technology for their realization [21]. Neural Networks, together with fuzzy sets, expert systems, gnostic theory of indefinite data or genetic algorithms, etc., are among the non-static higher methods of financial analysis [3].

In addition to the artificial neural networks evaluation, the researchers [4] argue that the inclusion of the competitive environment in evaluating businesses on the matter reveals necessary such as the ability to identify, understand, and adopt best practices and the opportunity to establish standards against which processes, services, and products can be compared and consequently be improved.

In this light, multilayer perceptron (MLP) neural networks are also used to analyze business growth as a branch of artificial neural networks. Moreover, the review of the business analysis framework, including management practices, suggests that artificial intelligence techniques should be used in future research.

Thus, supported by technological advances, neural network analysis models have become increasingly recognized as a robust methodology for investigating the factors that affect business risks and their growth. In the meantime, these kinds of analyses must also be implemented in construction business practice under a self-improvement context. To overcome this issue, we propose implementing a Multilayer Perceptron Analysis in assessing factors that impact construction businesses' growth through quantitative and qualitative variables in this research study. From an empirical point of view, this research can pave the way for other studies of similar nature.

III. Materials and Method

Through artificial neural networks models is simulated the functioning of the human brain. The development of these networking models is made possible by using the elementary computational units called Processing Elements (PE) [22]. The Input Layers, instead are the input neurons that receive the incoming stimuli (information). Input neurons process, according to a particular function called the Transfer function, distributes the result to the next level of neurons. Then, the input neurons forward the weighted information to all neurons of layer 2 (Middle Layers).

In this research, we use artificial neural network models to artificially simulate the physiological structure and functioning of human brain structures for analyzing firms' growth in the construction sector. One of the most popular ANNs is Multi-Layer Perceptron (MLP). For firm's growth analysis purposes, the most straightforward network of "customer patterns-processing elements" known as a perceptron, consists of a single neuron with “n” inputs and one output. The primary learning algorithm (even called the training process) of the perceptron analyzes the configuration (pattern) input and weighting patterns through synapses, deciding which category of output is associated with the configuration [23].

A. The Multilayer Perceptron Analysis

The neural network with one input layer, one or more layers of intermediate neurons, and an output layer is called the Multilayer Perceptron [24].Initially, in the Multilayer Perceptron analysis, the feed-forward signals propagate from input to output only through intermediate neurons to provide firm growth feedback. However, the Back Propagation learning algorithm is used. The Back Propagation learning algorithm calculates the appropriate syntactic weights between inputs and neurons of intermediate layers and between them and outputs, starting from random weights to them and making small changes, gradual and progressive, determined by estimating the error between the result produced by the network and the desired one [25]. Multilayer perceptron analysis, through a series of attempts, sometimes prolonged, allows modeling the weights that link the input (customers patterns) with output (start-up (0), growth (1), and maturity phases (2)) through the hidden layers of neurons. In order to provide the MLP analysis results in this research we used the statistical package SPSS 21.0 version.

B. *Research Sample*

This research explored 31 business data out of 85 business data collected. The data pertain to a panel of businesses operating in the trade sector as per the 2020-2021 period. For Multilayer Perceptron analysis training, these 31 businesses are also considered valid (refer to Table 1).

Table 1. Case Processing Summary

		N	Percent
Sample	**Training**	31	100.0%
Valid		31	100.0%
Excluded		54	
Total		85	

Source: Authors` estimation through SPSS

C. *Data Information*

The construction businesses data collected (see Table 2) are classified into Organizational characteristics (5 patterns) and Financial indicators (18 patterns).

The last ones refer to Liquidity (5), Operational Efficiency (4), Leverage (4), and Growth (5) patterns.

These data are provided from the National Registration Centre (NRC) and Credit Registry of Bank of Albania (CRBA) databases of the year 2021.

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Table 2. Research Variables Summary

		Variable	**Measurement**	**Abbr.**
	Organizational patterns	Administrator Gender	Administrator´s gender (female-0, male-1 and mixed genders-2)	AG
		Business Ownership	Business owner (administrator -0 or no administrator-1)	BO
		Equity Origin	Business equity origin (national-0, foreign-1 and joint-venture-2)	EO
		Ownership Gender	Ownership gender (female-0, male-1 and mixed gender ownership-2)	OG
		Borrower Status	Borrower Status (non-performing + 30 due days-0 /performing 0-29 due days-1)	BS
Financial patterns	*Liquidity indicator*	Current assets	Short term assets/Short term debts	CA
		Inventory	End of year inventory	INV
		Short term assets	Cash+ trade securities portfolio+ receivable accounts + inventory	STA
		Working capital	Short term assets- Short term debts	WC
		Short term debts	Payable accounts, short term loans	STD
	Op.efficiency indicators	Gross profit margin	Gross profit/Net sales	GPM
		Net profit margin	Net profit/Net sales	NPM
		Assets turnover	(Net profit + interest expenses)/Average equity	AT
		Return on equity	Net profit/Average equity	ROE
	Leverage indicators	Long term debt/equity ratio	Long term debt/equity ratio	LTDER
		Interest coverage ratio	Earnings before interest and taxes / Interest expenses	ICR
		Total Leverage ratio	Total debts/Total assets	LEV
		Long term debts	End of year long term debts	LTD
	Growth indicators	CV	Collateral value	CV
		Business size	Ln(total assets)	BoS
		Age of firm	Analysis period-Business registration period (start-up: 0-5Years/0; growth: (6-15Years/1;maturity:>15Years/2)	FA
		Return on assets	Net profit/Average assets	ROA
		Equity	Business equity	EQ

Source: NRC and CRBA elaborated data

D. *Network Information*

This research implements a Receiver Operating Characteristics (ROC curve) Analysis at a 95% confidence level as an initial step before building the multilayer perceptron neural network. Then, we implemented a multilayer perceptron network with 10 input layers patterns, 10 customers' patterns factors, and one covariate. The number of hidden layers is 1 and the number of units in hidden layers is 20. The activation function used is a hyperbolic tangent. This function produces an output value between 0 and 2. The intention is to classify businesses into start-up (0), growth (1), and maturity phase (2) according to their age. The error function used is the sum of squares.

IV. RESULTS

Results should be clear and concise. The most important features and trends in the results should be described but should not interpreted in detail.
The preliminary test executed on the data collected for business growth analysis is the one of Receiver Operating Characteristics (ROC curve) Analysis at

a 95% confidence level. The results provided show referring to firms' age considered as a dependent variable: the currents assets (0.605), working capital (0.589) (liquidity area indicators); gross profit margin (0.752), net profit margin (0.947), assets turnover (0.856), return on equity (0.968) (operational efficiency area indicators); long term debt/equity ratio (0.738), total leverage (0.563) (leverage area indicators); return on assets (0.899) (growth area indicators) can discriminate businesses growth in start-up (0), growth (1) and maturity phase (2). Therefore, we use only these variables (patterns), such as input layers, in our MLP analysis for further evaluation.

In the MLP analysis, we implemented the short-term assets as covariates considering that start-up (0) growth (1) and maturity phase (2), businesses in the construction sector differ in the number of short-term assets held for business continuity purposes and from an income generation point of view.

The MLP analysis network data shows that the number of units in the Hidden Layer is 20 (see Table 3), meaning that the configuration process is dynamic and complex. Straightforward, this confirms that the logic used above in developing the neural network on the matter is correct.

Table 3. Summary Multilayer Perceptron Network Information data

Input Layer	Factors	1	ILR-1 CA
		2	ILR-2 WC
		3	OE-3 GPM
		4	OE-5 NPM
		5	OE-6 AT
		6	OE-7 ROE
		7	RA-1 LTDER
		8	GA1-ROE
		9	RA-4 TOTAL LEV
		10	GA-1 ROA
	Covariates	1	STA
	Number of Units[a]		291
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		20
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	FA
	Number of Units		3
	Activation Function		Hyperbolic tangent
	Error Function		Sum of Squares

Source: Authors` estimation through SPSS

V. DISCUSSION

The MLP model summary results (see Table 4) demonstrate that incorrect predictions in response to the firm age variable are 0%, and the error function is too small (0.008). The training process has run too fast (00:00:00.182 seconds). In other words, the goal of the training process to find the set of weights values that cause the output from the neural network to match the actual target values is achieved. In this case, the predictions generated from MLP analysis match the actual firms' age values.

Table 4. Model Summary

Training	Sum of Squares Error	.008
	Percent Incorrect Predictions	.0%
	Stopping Rule Used	Training error ratio criterion (.001) achieved
	Training Time	00:00:00.182

Source: Authors` estimation through SPSS

Meanwhile, referring to the ROC curve and MLP analysis data, it can be evidenced the fact that for firms' age classification in start-up (0), growth (1), and maturity phase (2) have under the area results equal to 1. This fact is another indicator that confirms the validity of the MLP model in firms' growth analysis. In statistical terms, the classification of the dependent variable: Firms age, in the MPL analysis training phase shows that each of the classifications in start-up (0) is 3,2%; in growth (1) is 54,8% and in maturity phase (2) is 41,9% (100 % percent correct in three statutes).

This reconfirms that the MLP analysis used in firms' growth analysis is an objective approach. In addition to the calculation of the syntactic weights for each pattern/ variable used in MLP needed for the hidden layer estimation (from 1-20), the hidden layers' syntactic weights are obtained (as presented in Table 5) for the output estimation purposes [start-up (0), growth (1) and maturity (2) phase]. This provides a concrete estimation for each business profile concerning their growth approach.

Table 5. MLP –Parameter estimates for Hidden (1-20) layers

	Firm age		
	Start-up phase (0)	Growth phase (1)	Maturity phase (2)
Bias	0,209	1,150	0,569
H (1;1)	-0,168	0,055	0,284
H (1;2)	0,054	-0,314	0,219
H (1;3)	0,086	-0,169	0,078
H (1;4)	0,002	0,215	-0,148
H (1;5)	-0,068	-0,088	0,047
H (1;6)	0,044	0,290	-0,356
H (1;7)	-0,327	0,031	0,349
H (1;8)	0,212	0,306	-0,377
H (1;9)	0,205	-0,359	0,592
H (1;10)	-0,058	-0,444	0,513
H (1;11)	-0,187	0,021	0,021
H (1;12)	0,285	-0,431	0,071
H (1;13)	-0,095	-0,081	0,376
H (1;14)	-0,123	0,009	0,123
H (1;15)	0,133	-0,876	0,617
H (1;16)	-0,049	-0,185	0,019
H (1;17)	0,064	-0,035	-0,205
H (1;18)	-0,005	-0,177	0,199
H (1;19)	-0,097	0,052	0,238
H (1;20)	0,210	-0,141	-0,166

Source: Authors` estimation through SPSS

Closely referring to MLP analysis, as per: incorrect predictions (0%), training time processing (00:00:00.182 seconds), dependent variable: Firms age under the area value [in start-up (0), growth (1) and maturity (2) phase] equal to 1 and to the classification correct percentage (100%) in the training process for the dependent variable. Thus, it can be deduced that the implemented approach for construction firms growth analysis purposes is the adequate one.

VI. CONCLUSION

This research paper explored the MLP approach in firms' growth analysis in the construction sector. MLP has not been tested for firms' growth analysis purposes. Therefore in this study, we have proposed and tested a simple MLP analysis with only one hidden layer while the number of units calculated in hidden layers is 20 (named neurons). The statistical package used (SPSS 21.0 version) has self-calculated the number of neurons considering the variables/patterns, which resulted in being discriminator according to our preliminary ROC (curve) analysis by using as dependent variable: Firms' age.

The reason is that if an inadequate number of neurons are used, the network will be unable to model complex data, and the resulting fit will be poor. Furthermore, if too many neurons are used, the training time may become excessively long, and worse, the network may overfit the data. Referring to the results achieved (100% correct predictions were made) it can be recognized the MLP advantages in analysing construction firms growth analysis.

In this MLP approach developed for construction firms, the most relevant patterns that govern their age as a dependent variable [start-up (0), growth (1), and maturity phase (2)] refer to:

- liquidity area (current assets and working capital);
- operational efficiency area (gross profit margin, net profit margin, asset turnover, and return on equity);
- leverage area (long-term debt/equity ratio; total leverage);
- growth area (return on assets).

In this light should also be highlighted the fact that independently from the firm's age, the factors over which the construction businesses trust their growth potential are: current assets, gross profit margin, net profit margin, asset turnover and return on equity. In other words, operational efficiency indicators are the crucial elements ensuring growth in construction businesses. Comprehensively from the fiscal policy point of view is convenient to apply a more relaxed taxation rate for those businesses in a start-up than for those in the growth and maturity phase.

Meanwhile, it should be evidenced the fact that construction businesses' organizational structure and their gender profile do not represent any influence on growth performance.

According to the implemented MLP results, it can be evidenced the fact that it is also able to analyze and interpret complex data, as well as reveal hidden relations between them. The last one is the most particular feature that governs these approaches properly, constituting a need for more transparency in evaluating syntactic weights.

The other limitation of MLP approaches is that it needs large data samples for training. Furthermore, considering the complexity of these approaches and business exigencies, the researchers should go deeper with additional analysis referring to business size (according to fiscal classification) and various sectors of activity.

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