Methods and Models of Machine Learning in managing the market value of the company

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Abstract. The paper is devoted to a conceptual approach to the construction of a set of models for identifying a class of peer companies when choosing multipliers in the process of assessing the market value of companies that are not listed on stock exchanges. The proposed approach is based on machine learning methods (clustering and classification) and implemented on data from 113 IT companies listed on the S&P500. The prognostic efficiency of machine learning methods is considered when constructing a class identification model based on "noisy" data. Models of identification of a class of peer companies have been developed, the choice of values of interval multipliers for the analyzed firms (which are not included in listings) has been substantiated, which makes it possible to improve the quality of assessing the market value of their business.

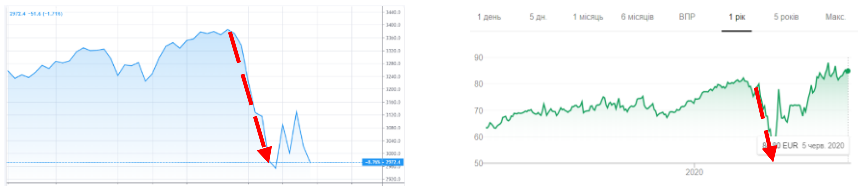
Keywords: Class identification of peer company, Classification, Clustering, Company value appraisal, Machine learning methods, Market approach, Model, Multiplier

1. Introduction

The modern conditions for the functioning of companies are characterized by a post-crisis syndrome associated with the effect of the economic "shock" induced by COVID-19. Unfortunately, the consequences of this "shock" turned out to be deeper than predicted. In particular, the IMF has updated the forecast of the global economic decline from 3% to 4.9% [1]. The NBU kept the forecast for the decline of the Ukrainian economy at the level of 6%, but the analysis of statistical data shows that the depth of the crisis will be more severe [2].

Undoubtedly, the impact of "shock" has an asymmetric effect on various sectors of the economy, spheres of activity, enterprises of various spheres of activity, forms a reverse impulse to reduce the level of stability of systems of a higher level of the hierarchy, in particular, of the banking system, certain elements of which have a concentration of assets in certain sectors. Under these conditions, the search for new methods and mechanisms of financial management, aimed at reducing both individual and systemic risks, becomes relevant in systems of different levels of the hierarchy.

One of the basic areas of financial management in corporate systems is market value management. In particular, the priority of this area is confirmed by the fact that maximizing the company's market value (maximizing the income of the company's owners) is considered as the main criterion indicator of the effectiveness of financial decisions [3-4]. It should be noted that the “shock” induced by COVID-19 caused a sharp decline in the market value of companies and a collapse of stock indices, which, in particular, is demonstrated by the charts shown in Fig. 1 [5].



a) S&P 500 Index dynamics (2020)

b) Euronext Index dynamics (2020)

Fig. 1. Dynamics of stock indices due to the "shock" induced by COVID-19

The significant volatility of the value of financial assets due to the panic expectations of investors regarding the duration of the recovery of the level of business activity and the profitability of companies' activities forces us to look for new technologies for monitoring and of proactive management of the risk of loss of long-term financial stability, loss of financial security due to a decrease in market value, aimed at preventing crisis situations.

It must be said that managing the market value of a company involves solving a triad of such functional tasks as assessing and monitoring the dynamics of the company's market value; diagnostics of the factors that determine the change in the market value of the company; formation of a financial strategy aimed at ensuring sustainable development of the company and maximizing market value. Among the triad of identified tasks, the basic task, the quality of the solution of which largely impacts on the efficiency of managing the market value of the company as a whole, is the assessment and monitoring of the dynamics of the market value.

2. Literature Review

The problem of developing theoretical and methodological approaches to assessing the market value of a company is widely considered in the scientific literature [3-4, 6-12]. In particular, the cost, profitable and comparative (market) approach to assessing the value of a company is traditionally distinguished. The cost approach is based on an element-by-element assessment of the market value of a company's assets or replacement cost, which implies an assessment of the cost of creating a company with a similar competitive position in the market [6]. Typically, this approach is used by financial institutions for insurance purposes, since it shows the lower bound of the company's value. The cost approach is used in combination with the income approach, which allows assessing the company's ability to generate profit [3-4]. The profitable approach is interesting, first of all, to investors, as it makes it possible to assess the payback periods of a business investment project and the profitability of such a project. The market (comparative) approach to assessing the value of a company (assessing the value of a business) is the most common and attractive for a wide range of stakeholders, including company management, as it is based on the analysis of actual sales data. Further, it will be considered exactly the market approach to assessing the value of a business.

It should be noted that a large number of scientific works are devoted to the analysis of factors affecting the market value of corporations, while the factors under consideration reflect both financial and non-financial aspects of company policy. In particular, work [7] examines the influence of the level of transparency of a company on its market value. The work [8] examines the impact of the quality of personnel management and labor conflicts on the market value of the company. The asymmetric effects of this factor on the market value of companies with different scales of activity are shown. The factor of the quality of human capital and the quality of management, as well as the innovation policy of the company, were identified as dominant for the formation of added value in the era of the fourth industrial revolution in the work [9]. The level of transparency, investment in the development of information systems of corporations, an increase in the level of digitalization is considered as a factor of corporate sustainability and growth of market value in the study [10]. The priority of the digitalization factor for the formation of positive dynamics of changes in the market value, but in the context of a certain industry (on the data of logistics companies) is emphasized in [11]. Along with the works affecting the strategic management loop, a large number of works are devoted to the analysis of the influence of factors at the tactical level. In particular, publication [12] examines the impact of policies and tools for managing financial and operational risks on the market value of a company.

Noting the unconditional relevance and effectiveness of the topics and approaches touched upon by the authors of the above works, it should be noted that approaches to assessing the market value of companies with different scales of activity have not been fully considered. It should be noted that the use of the income approach, which requires the development of adequate forecasts of the financial flows of companies for the medium term in the context of the post-crisis syndrome and a high level of turbulence in the external environment, as well as the cost-based approach, which requires an expensive item-by-item assessment of the value of assets, is difficult for medium-sized companies.

As mentioned earlier, the market approach to business valuation involves the analysis of the value of similar companies, the data of market transactions for which are known. Estimating the value of a company using the market method includes the following main stages: 1) selection of peer enterprises; 2) financial analysis and comparison, recognition of the class of a peer enterprise; 3) selection and calculation of estimated multipliers; 4) application of multipliers to the evaluated enterprise; 5) amendment to the total value.

It should be noted that today the issues of developing a model for identifying a class of peer enterprises are poorly considered, the data of which can be used to calculate the values of the multipliers for the evaluated company, which is not listed on stock exchanges. This task can be effectively solved using machine learning methods, which are further discussed in this work.

3. Methodology and Data

The proposed methodological approach to assessing the market value of a company based on machine learning methods includes the following main modules: 1) module 1 – classification of peer companies; 2) development of a model for identifying a class of peer companies and the choice of multipliers; 3) recognition of the class of evaluated companies and assessment of market value (Table 1). The content of each module is considered below.

Table 1. Main modules of the conceptual approach

Modules	*Methods*	*Models*
Module 1. *Classification of peer companies* 1.1. Classification of companies based on hierarchical agglomerative methods, determination of the number of clusters 1.2. Classifying companies using iterative methods 1.3. Comparison of the quality of classification and selection of the final variant of the partition	Hierarchical agglomerative clustering; Iterative Cluster Analysis Techniques	Peer company classification model (M1)
Module 2. *Development of a model for identifying a class of peer companies* 2.1. The construction of a discriminant model for identifying a class of peer enterprises 2.2. Development of a neural network model for identifying a class of peer companies 2.3. Comparison of the quality of models and the choice of a class identification model	Discriminant Analysis Logit-, probit- regression Neural network modelling	Model for identifying a class of peer companies and choosing multipliers (M2)
Module 3. *Recognition of the class of evaluated companies and assessment of market value* 3.1. Recognition of the class of the evaluated company 3.2. Choosing a multiplier 3.3. Value estimation	Market (comparative) method of assessing the value of the company	Model of company value appraisal (M3)

In the *first module*, the grouping of peer companies is carried out. The main tasks of this module are: formation of a system of indicators by which comparison is carried out, assessment of their information content; grouping of peer companies.

A preliminary list of indicators by which the comparison of analogous companies is carried out is formed on the basis of a review of literary sources. To assess the information content and filter the generated list of indicators, various methods can be used: methods based on auto-information criteria; methods focused on the assessment of information content based on the analysis of cause-and-effect relationships. The first group of methods makes it possible to assess the informational significance of indicators, to reveal hidden properties and patterns in large volumes of raw data, in the case when the structure of the input and output data set is unknown. The advantage of the second group of methods is the ability to reduce the dimension of the information space of attributes based on the analysis of cause-and-effect relationships of a set of input and output indicators. The choice of the method is determined by the complete or incomplete provision of information, the sample size, the structure of the set of input and output indicators, and the presence of a training sample. Taking into account the limitations on the information security of indicators, the methods of expert analysis are used in the work to form a system of diagnostic indicators. More detailed procedures for filtering the system of indicators are given in [13-14].

The resulting system of indicators is the basis for grouping peer companies using cluster analysis methods [15-16]. Hierarchical agglomerative and iterative methods were used to construct the grouping. Hierarchical agglomerative methods give only a conditionally optimal solution in a certain subset of local partitions (clusters). However, the advantage of these methods is the simplicity of calculations and interpretation of the results obtained. The essence of hierarchical agglomerative methods lies in the fact that at the first step, each sample object is considered as a separate cluster. The process of combining clusters occurs sequentially: based on the distance matrix or similarity matrix, the closest objects are combined. The clustering results, presented in the form of a dendrogram, make it possible to select the number of clusters at which the total intergroup variance will take the maximum value. This number of clusters is used to select the initial conditions for the iterative algorithm of "k-means" method. After the completion of the classification procedures, it is necessary to evaluate the results obtained. For this purpose, a certain measure of the classification quality (quality functional) is used. The best partition according to the chosen functional should be considered the one, which achieves the extreme value of the objective function – the quality functional [16]. The result of the implementation of the tasks of the first module is a model for the classification of peer companies (M1), which are characterized by different levels of interval and moment multipliers for assessing the market value.

In the *second module*, a model for identifying a class of peer companies (M2) is developed. To solve this task with the subsequent selection of the best one, discriminant analysis models, probit-logit analysis models, and neural network modelling are used [14-17]. The discriminant analysis procedure involves assessing the discriminant power of variables, selecting statistically significant discriminator variables, constructing a system of discriminant functions, and assessing the quality of recognition. Logit-, probit- analysis is based on econometric modeling technology and includes: determination of the optimal list of variables; development of a logit-probit model; assessment of the quality of the classification. The advantage of artificial neural networks is the ability to simulate various processes with a predetermined accuracy, easy learning and the ability to work with noisy data. The best class identification model is selected based on a comparison of the recognition quality.

The content of the *third module* is the identification of the class of the evaluated companies and the choice of the multiplier for assessing the market value. In this module, based on the financial data of the evaluated company, the class of peer companies is recognized, the shares of which are quoted on the stock exchange. Identification of a class of similar companies allows you to select a multiplier and apply it to the financial base of the evaluated company (a company that is not included in the listing) to determine the real market value based on the M3 model.

Thus, the methodological approach proposed above makes it possible to develop a set of models for identifying a class of peer companies and increases the validity and quality of management decisions regarding the choice of a price multiplier used to assess the value of a business.

The proposed approach has been tested on data from 113 IT companies listed on the S & P500 [18]. Further, the results of its implementation are considered.

4. Results and analysis

In accordance with table 1 in the 1st module a list of indicators is formed, and a model for the classification of IT companies is built using the methods of hierarchical agglomerative and iterative cluster analysis. To compare the evaluated companies and their peers, based on the proposed filtering procedures, the following indicators were selected: x1 – Profit Margin, %; x2 – Operating Margin, %; x3 – Current ratio; x4 – Total Debt / Equity; x5 – Short ratio. Fragment of the initial data is presented in table 2.

Table 2. Fragment of initial data

No.	Company	Profit Margin	Operating Margin	Current ratio	Total Debt/Equity	Short ratio
1	APPLE INC	37,88	24,19	1,47	1,69	1,43
2	ACCENTURE PLC	31,64	14,8	1,4	0,21	1,4
3	Adobe Inc,	40,88	32,93	1,68	35,49	1,63
4	Advanced Micro Devices Inc	13,27	10,17	2,28	14,95	1,37
…	…	….	….	…	…	…
113	XEROX	38,47	9,79	1,42	0,76	1,18

To construct the grouping at the initial step, one of the methods of hierarchical clustering was used - the Ward method, which allows minimizing the total intraclass variance. The Euclidean metric was considered as a measure of distance. The classification dendrogram obtained using the program “Statistica” is shown in Fig. 2.

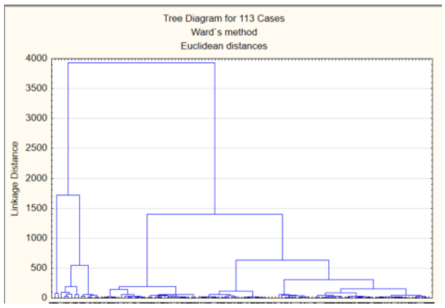


Fig. 2. Dendrogram of classification of IT companies

Analysis of the data shown in Fig. 2, allows us to conclude that it is expedient to have 2 or 3 cluster partitioning of the initial set of IT companies. Since the minimum value of the classification quality functionals is typical for a 3-cluster partition, the results of this grouping are presented below.

The found value of the number of clusters was specified as an exogenous parameter when determining the composition of clusters using the iterative algorithm of the "k-means" method. The results of analysis of variance, reflecting the significance of the variables for classification, are shown in Fig. 3.

	Analysis of Variance (Spreadsheet1)					
Variable	Between SS	df	Within SS	df	F	signif. p
x1	55,75737	2	56,24263	110	54,52546	0,000000
x2	28,25557	2	83,74444	110	18,55713	0,000000
x3	64,19258	2	47,80742	110	73,85030	0,000000
x4	12,88563	2	99,11436	110	7,15043	0,001204
x5	49,95906	2	62,04094	110	44,28928	0,000000

Fig. 3. ANOVA results

The data in Fig. 3 shows that the hypothesis of significant differentiation of clusters is accepted with a 99% confidence level. The mean values of the indicators are given in Fig. 4.

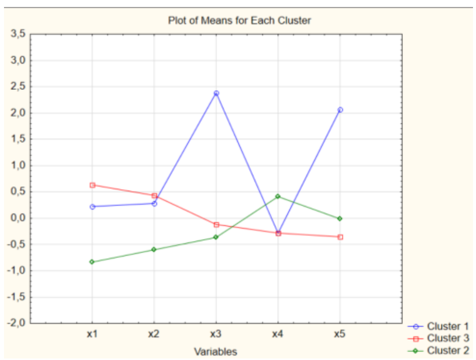


Fig. 4. Graph of mean values of indicators in clusters

As can be seen from Fig. 4, *cluster 3* was formed by IT companies with a high level of corporate sustainability. Companies in this cluster are characterized by high gross and operating margins, low levels of debt for companies of the analyzed industry focus, and an average level of current liquidity. That is these are profit-oriented companies with a sufficient level of sustainability. *Cluster 1* includes companies with an average level of both gross and operating margins, a high level of current and absolute solvency, and a low level of debt. This cluster was formed by companies with a sufficient level of corporate stability. *Cluster 2* companies have the worst characteristics: there is a significant gap in the level of marginality in comparison with companies in cluster 3 and cluster 1, the highest level of debt in the surveyed set of companies, the average level of absolute liquidity, but its lowest short-term level. Thus, this cluster was formed by companies with a low level of corporate sustainability.

Analysis of the composition of the clusters made it possible to conclude that the classification obtained is correct. In particular, companies in the cluster with a high level of corporate stability (*cluster 3*) included such companies as FACEBOOK INC (C_75), NVIDIA CORP (C_98), TWITTER (C_108), etc (Fig. 5). Companies with a high level of corporate stability account for 24% of companies in the analyzed population.

Case No.	Distance
C_5	0,980472
C_7	1,418798
C_10	0,810073
C_33	1,325040
C_41	0,688003
C_75	0,921229
C_89	1,097040
C_98	0,451636
C_106	0,551284
C_108	1,817798

Fig. 5. The composition of the first cluster

In the second module, a model for recognizing a class of analogous companies was built. Input variables (training sample) are: x1 – Profit Margin, %; x2 – Operating Margin, %; x3 – Current ratio; x4 – Total Debt / Equity; x5 – Short ratio, and the resulting variable is the class of the company that is listed on the stock exchange: 1st class – average level of corporate stability, 2nd class – low level of corporate stability, 3rd class – high level of corporate stability. To build a model, as mentioned above, with the subsequent selection of the best one, the methods of discriminant analysis, logistic regression, methods of neural network modelling were used.

The results of estimating the discriminant power of variables are shown in Fig. 6.

	Discriminant Function Analysis Summary (Spreadsheet1) No. of vars in model: 5; Grouping: Cluster (3 grps) Wilks' Lambda: ,28654 approx. F (10,212)=18,405 p<0,0000					
N=113	**Wilks' Lambda**	Partial Lambda	F-remove (2,106)	p-value	Toler.	1-Toler. (R-Sqr.)
x1	0,307936	0,930507	3,95818	0,021986	0,782567	0,217433
x2	0,308426	0,929030	4,04875	0,020210	0,895461	0,104539
x3	0,312865	0,915850	4,86975	0,009477	0,819713	0,180287
x4	0,306699	0,934262	3,72927	0,027217	0,775775	0,224226
x5	0,471624	0,607554	34,23502	0,000000	0,921182	0,078818

Fig. 6. Assessing the Significance of Discriminant Variables

The values of the Wilkes λ-statistic, the F statistic indicates the significance of the variables for recognition. The strongest discriminator is the variable x5 – absolute liquidity, x3 – current liquidity. The criteria for the static significance of the canonical discriminant variables are shown in Fig. 7.

Roots Removed	Chi-Square Tests with Successive Roots Removed (Spreadsheet1) Eigen-value	Canonicl R	Wilks' Lambda	Chi-Sqr.	df	p-value
0	1,820805	0,803425	0,286537	134,9879	10	0,000000
1	0,237218	0,437876	0,808265	22,9895	4	0,000127

a) criteria for the static significance of discriminant canonical functions

Variable	Factor Structure Matrix (Spreadsheet1) Correlations Variables - Canonical Roots (Pooled-within-groups correlations) Root 1	Root 2
x1	0,031571	-0,812528
x2	-0,099549	-0,776996
x3	-0,480491	-0,056757
x4	-0,210606	0,157748
x5	-0,887475	0,130153

b) factorial structure of canonical variables

Fig. 7. Characteristics of Canonical Discriminant Variables

Fig. 7 allows to conclude about the statistical significance of the canonical discriminant functions. The first canonical discriminant function has a higher information load, the factor structure of which makes it possible to conclude that it reflects the level of short-term and medium-term financial stability of the company. Negative values of factor loadings indicate that the lower the value of the first canonical discriminant variable – the higher the level of the company's stability. The second variable has a much lower discriminant power and is “responsible” primarily for the level of marginality. Negative values also allow us to give the following interpretation: the lower the value of the canonical variable – the higher the level of profitability of the company.

The distribution of objects in the space of canonical variables is shown in Fig. 8.

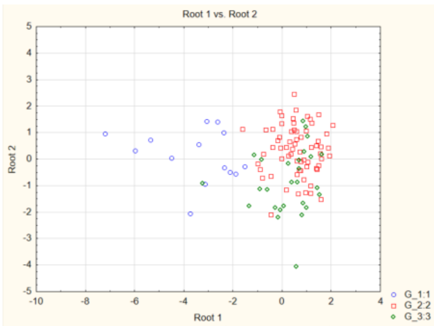


Fig. 8. Distribution of objects in the space of canonical variables

Fig. 8 shows the higher discriminant power of the first canonical variable, which "distinguishes" the companies with aggressive and conservative financial management models. The boundaries of cluster 2 and cluster 3 are not clear-cut; nevertheless, most of the objects in cluster 3 are characterized by a high level of margins in comparison with companies in cluster 2 and cluster 1.

The parameters of the classifying discriminant functions are shown in Fig. 9.

Variable	Classification Functions; grouping: Clu G_1:1 p=,12389	G_2:2 p=,63717	G_3:3 p=,23894
x1	0,0706	0,05822	0,09305
x2	0,2036	0,13962	0,20964
x3	1,6959	0,60024	0,62569
x4	0,0219	0,00930	0,01064
x5	4,3780	1,44773	1,67359
Constant	-24,1967	-4,67263	-9,21664

a) parameters of classifying discriminant functions

Classification Matrix (Spreadsheet1)
Rows: Observed classifications
Columns: Predicted classifications

Group	Percent Correct	G_1:1 p=,12389	G_2:2 p=,63717	G_3:3 p=,23894
G_1:1	92,85714	13	1	0
G_2:2	94,44444	0	68	4
G_3:3	40,74074	1	15	11
Total	81,41593	14	84	15

b) classification matrix

Fig. 9. Parameters and quality criteria of classifying discriminant functions

Fig. 9 show the acceptable recognition quality for the system of discriminant functions as a whole: the percentage of correct classification is 81.41%. However, the quality of recognition of the elements of the 3rd cluster is low. To improve the quality of the model, the “outliers” points were removed from the initial sample; a fragment of their identification is shown in Fig. 10.

Classification of Cases (Spreadsheet1)
Incorrect classifications are marked with *

Case	Observed Classif.	1 p=,12389	2 p=,63717	3 p=,23894
1	G_2:2	G_2:2	G_3:3	G_1:1
2	G_2:2	G_2:2	G_3:3	G_1:1
* 3	G_3:3	G_2:2	G_3:3	G_1:1
* 4	G_3:3	G_2:2	G_3:3	G_1:1
5	G_1:1	G_1:1	G_2:2	G_3:3
6	G_2:2	G_2:2	G_3:3	G_1:1
7	G_1:1	G_1:1	G_3:3	G_2:2
* 8	G_3:3	G_2:2	G_3:3	G_1:1
9	G_2:2	G_2:2	G_3:3	G_1:1
* 10	G_1:1	G_2:2	G_3:3	G_1:1
11	G_2:2	G_2:2	G_3:3	G_1:1
12	G_2:2	G_2:2	G_3:3	G_1:1
13	G_2:2	G_2:2	G_3:3	G_1:1
* 14	G_3:3	G_2:2	G_3:3	G_1:1
15	G_2:2	G_2:2	G_3:3	G_1:1

Fig. 10. Testing for outlier points

The parameters and quality criteria of the classifying functions built on the truncated data are shown in Fig. 11.

Variable	Classification Functions; grouping: Clu G_1:1 p=,13580	G_2:2 p=,76543	G_3:3 p=,09877
x1	0,1157	0,07918	0,1761
x2	0,3211	0,21663	0,4240
x3	2,0540	0,73012	0,4217
x4	0,0238	0,00973	0,0139
x5	6,7302	2,35663	2,9542
Constant	-34,0213	-6,37924	-19,3788

a) parameters of classifying discriminant functions

Classification Matrix (Spreadsheet1)
Rows: Observed classifications
Columns: Predicted classifications

Group	Percent Correct	G_1:1 p=,13580	G_2:2 p=,76543	G_3:3 p=,09877
G_1:1	100,0000	11	0	0
G_2:2	100,0000	0	62	0
G_3:3	100,0000	0	0	8
Total	100,0000	11	62	8

b) classification matrix

Fig. 11. Parameters and quality criteria of classifying discriminant functions

As can be seen from Fig. 11, the recognition error is 0%, which allows us to conclude that it is possible to use the constructed system of models for a class recognition of peer companies in the process of assessing the market value of companies that are not listed on stock exchanges.

It should be noted that the data in Fig. 8 indicates the presence of a significant array of "noisy" data, therefore, models of neural networks were considered as an alternative model for class recognition. The neural network modelling results are shown in Fig. 12.

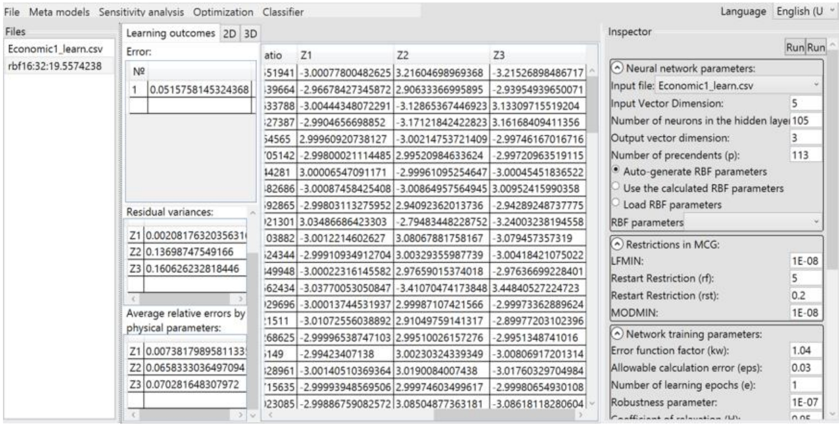


Fig. 12. The results of neural network modelling using ROD&IDS

The construction of the model was carried out in the interactive computer decision support system «Methods of nonlinear estimation in multicriteria problems of robust optimal design and diagnostics of systems in the conditions of parametric a priori uncertainty" ("ROD & IDS") [19].

As a result of training the neural network, the classification error was less than 7%.

In the *third module*, based on the built set of models, the recognition of a class of analogous companies for 5 IT companies operating in the Ukrainian market was carried out. The results of class recognition are shown in Fig. 13.

Case	Classification of Cases (Spreadsheet1) Incorrect classifications are marked with *			
	Observed Classif.	1 p=,13580	2 p=,76543	3 p=,09877
73	G_1:1	G_1:1	G_2:2	G_3:3
74	G_2:2	G_2:2	G_3:3	G_1:1
75	G_2:2	G_2:2	G_3:3	G_1:1
76	G_2:2	G_2:2	G_3:3	G_1:1
77	G_3:3	G_3:3	G_2:2	G_1:1
78	G_2:2	G_2:2	G_3:3	G_1:1
79	G_2:2	G_2:2	G_3:3	G_1:1
80	G_2:2	G_2:2	G_3:3	G_1:1
81	G_3:3	G_3:3	G_2:2	G_1:1
82	---	G_2:2	G_3:3	G_1:1
83	---	G_2:2	G_3:3	G_1:1
84	---	G_2:2	G_3:3	G_1:1
85	---	G_2:2	G_3:3	G_1:1
86	---	G_2:2	G_3:3	G_1:1

a) based on discriminant functions

Case	Squared Mahalanobis Distances from Group Centroi Incorrect classifications are marked with *			
	Observed Classif.	G_1:1 p=,13580	G_2:2 p=,76543	G_3:3 p=,09877
73	G_1:1	23,30639	76,03937	77,89402
74	G_2:2	28,56758	3,93089	9,16264
75	G_2:2	14,01122	3,66545	3,78794
76	G_2:2	41,63499	3,06785	10,74172
77	G_3:3	19,36289	8,69997	0,67969
78	G_2:2	33,71232	1,76545	5,59674
79	G_2:2	23,84899	0,70159	10,18370
80	G_2:2	29,48803	4,29298	5,00092
81	G_3:3	32,80593	7,57325	0,92486
82	---	59,52109	26,42366	39,94063
83	---	32,88590	5,91265	15,68729
84	---	35,76473	3,77519	21,39954
85	---	54,60813	33,32392	45,31983
86	---	37,21623	2,58751	9,21641

b) based on distances to cluster centroids

Case	Posterior Probabilities (Spreadsheet1) Incorrect classifications are marked with *			
	Observed Classif.	G_1:1 p=,13580	G_2:2 p=,76543	G_3:3 p=,09877
73	G_1:1	1,000000	0,000000	0,000000
74	G_2:2	0,000001	0,990655	0,009345
75	G_2:2	0,000896	0,890970	0,108134
76	G_2:2	0,000000	0,997226	0,002774
77	G_3:3	0,000106	0,123189	0,876705
78	G_2:2	0,000000	0,981355	0,018645
79	G_2:2	0,000002	0,998873	0,001125
80	G_2:2	0,000001	0,916953	0,083046
81	G_3:3	0,000000	0,218146	0,781854
82	---	0,000000	0,999850	0,000150
83	---	0,000000	0,999028	0,000972
84	---	0,000000	0,999981	0,000019
85	---	0,000004	0,999675	0,000320
86	---	0,000000	0,995331	0,004669

c) based on posterior probabilities

Fig. 13. Recognition results of a class of peer companies

As can be seen from Fig. 13, the analyzed companies belong to cluster 2. The mean values of the multiples for each cluster of peer companies are shown in Table 3.

Table 3. Mean values of multiples for clusters of peer companies

Cluster	Interpretation	Multiplier - Enterprise Value/Revenue	Multiplier - Enterprise Value/EBITDA
Cluster 3	High level of corporate sustainability	15,53	49,29
Cluster 1	Medium level of corporate sustainability	7,78	19,53
Cluster 2	Low level of corporate sustainability	4,19	14,56

Thus, when assessing the market value of the analyzed companies, the following values of the interval multipliers should be used: Enterprise Value / Revenue – 4.19; Enterprise Value / EBITDA – 14.56. It should also be noted that the proposed set of models can be useful in the formation and calibration of the strategy for managing the market value of the analyzed companies, since it allows one to determine the target values of the variables that determine the company's transition to a higher cluster.

5. Conclusions

The conducted research led to the following conclusions:

a conceptual approach to the construction of a set of identification models for a class of peer companies is proposed, which, based on the use of machine learning methods, makes it possible to increase the validity of management decisions regarding the choice of interval and moment multipliers when assessing the value of companies that are not listed on stock exchanges;

models for classifying IT companies by the level of corporate sustainability have been developed;

models of class identification of peer companies have been developed. The use of models for recognizing the class of evaluated companies made it possible to justify the choice of multiplier values that should be applied to the financial base of the analyzed companies.

As areas for further research, it is necessary to highlight the analysis of the combinatorial application of the proposed conceptual approach and methods of simulation modelling, system dynamics, scenario modelling for the formation of a risk-resistant strategy for managing the company's market value.

References

1. World Economic Outlook Update, https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020, last accessed June, 2020.

2. The NBU maintained the forecast of GDP decline by 6% in 2020, https://www.epravda.com.ua/news/2020/10/22/666521/, last accessed 2020/10/22.
3. Zyma, A.: Modelling the competitiveness of an industrial enterprise in an unstable economic environment. Dis. for a scientific degree Ph.D. Donetsk: DONN, 197 p. (2013).
4. Mykhaylyk, D., Levitskiy, S., and Shevchenko, E.: Modelling the financial stability of integrated structures in mergers and acquisitions. Journal of Economic Reforms, No. 2, 56-69 (2017).
5. Free Stock Charts, Stock Quotes and Trade Ideas – TradingView, https://www.tradingview.com
6. Minyeeva, D.: Market value of an enterprise as the main indicator of strategic development, https://cyberleninka.ru/article/n/rynochnaya-stoimost-predpriyatiya-kak-glavnyy-pokazatel -strategicheskogo-razvitiya?gclid=EAIaIQobChMIvN7QgamM7gIV4wZ7Ch3saQKOEA AYASAAEgKlEPD_BwE
7. Weiling, S., Xin, F.: The Correlation Research between Voluntary Information Disclosure and Corporate Value of Listed companies of Internet of Things. Procedia Computer Science, https://reader.elsevier.com/reader/sd/pii/S1877050917315879?token=8436568B093CD1D9796F7674256923C3141CEE842C3E032A5C074864E4FB1BAEB0666A27D86E173C51DC6C11B6ACD7A6, Volume 112, 1692-1700 (2017).
8. Afik, Z. & Haim, R. & Lahav, Y.: Advance notice labor conflicts and firm value—An event study analysis on Israeli companies. Finance Research Letters, Elsevier, vol. 31(C) (2019).
9. Xin Li Safia, Nosheen Xue Gao: Value creation during fourth industrial revolution: Use of intellectual capital by most innovative companies of the world. Technological Forecasting and Social Change. Technological Forecasting and Social Change, Volume 163, https://doi.org/10.1016/j.techfore.2020.120479 (2021).
10. Ricci, F., Scafarto, V. & Tron, A.: Value relevance of digitalization: The moderating role of corporate sustainability. An empirical study of Italian listed companies. Journal of Cleaner Production, v. 276, 123-282 (2020).
11. Liu, W., Wang, S., & Zhang, J.: Effect of intelligent logistics policy on shareholder value: Evidence from Chinese logistics companies Transportation Research Part E: Logistics and Transportation Review (2020).
12. Azadeh Hadian Cahit Adaoglu: The effects of financial and operational hedging on company value: The case of Malaysian multinationals. Journal of Asian Economics. Journal of Asian Economics, Vol. 70, 2020, 1-66 (2020).
13. Klebanova, T., Guryanova, L., & Shevchenko, I.: Model basis of the early warning and localization of crises in economic systems of territories Actual problems of economics, No. 3 (153), 201–211 (2014).
14.Guryanova L., Klebanova, T., & Trunova, T.: Modelling the financial strategy of the enterprise in an unstable environment. Econom Studies Journal, Issue 3, 91-109, (2017).
15. Kyzym, N., & Klebanova, T.: Models for assessing, analyzing and forecasting socio-economic systems. Monograph, Kh.: FLP Pavlenko A.G., ID "INZHEK" (2010).
16. Guryanova, L., Milevskiy, S., Bogachkova, L., Lytovchenko, I., & Polyanskiy, V.: Models of assessment and analysis in security management systems. The 5th International Scientific-Practical Conference "Problems of Infocommunications. Science and Technology", PIC S&T: IEEE, ` October 9-12, Kharkiv, Ukraine: Institute of Electrical and Electronics Engineers, Inc., 202-209, https://ieeexplore.ieee.org/document/8632066 (2018)

17. Strilets, V., Bakumenko, N., Donets, V., Chernysh, S., Ugryumov, M., &. Goncharova, T.: Machine Learning Methods in Medicine Diagnostics Problem. ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer. Proceedings of the 16th International Conference on ICT in Education, Research and Industrial Applications (ICTERI2020). Integration, Harmonization and Knowledge Transfer, Volume II: Workshops. Kharkiv, Ukraine, 89-101 (2020).
18. S&P500, https://finance.yahoo.com/quote/ACIW/key-statistics?p=ACIW
19. Ugryumov, M., Menyailov, E., Chernysh, S., & Ugryumova, K.: Computer program "Methods of nonlinear estimation in multicriteria problems of robust optimal design and diagnostics of systems in the conditions of parametric a priori uncertainty (methodology, methods, techniques and their computer support systems and decision making) («ROD&IDS»). Certificate of registration of copyright to the work № 82875. Copyright and related rights. Official bulletin. Kyiv: Ministry of Economic Development and Trade of Ukraine, No. 51, 403 p. (2018).