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1. CURRENT SITUATION OF THE STUDIED PROBLEM

The term *magic square* (depicted on figure 1) was firstly used in macroeconomics sphere by German economist and former minister of finance Karl Schiller [1]. It is the diagram with four perpendicular axes on which are depicted a country's main macroeconomics indicators: gross domestic product (GDP) growth rate, consumer prices inflation rate, unemployment rate and balance of trade expressed as a portion of GDP [2]. The area of quadrangle is used for relative comparison between countries. The higher quadrangle area means the better economic performance of the examined country. The idea of economic performance evaluation based on the stated indicators was introduced by Nicolas Kaldor (born Miklós Káldor), Hungarian economist [3].

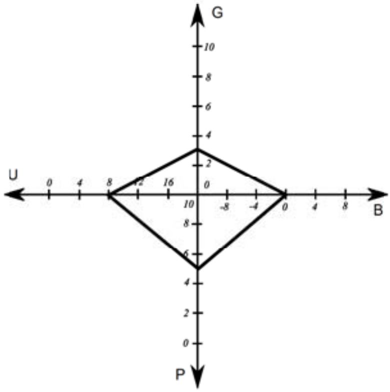

Figure 1: The example of Magic Square (values in percent)
(G - GDP growth rate, U - unemployment rate,
P - inflation rate, B - trade balance)

This chart (figure 1) is the special case of a spider diagram (radar chart) where the axes count can be higher than four. The disadvantage is that axes do not have the zero point in intersection and the quadrangle area is changing based on zero location on each axis. The example of another disadvantage is that consumer prices inflation rate below zero (deflation) is not desirable [4], but the quadrangle area is growing in this case.

The similar principle of evaluation and comparison can be used also in case of companies. There will be several axes with performance indicators (figure 2) and a company with higher polygon area has better performance (is rated higher) than company with lower polygon area. To avoid above stated disadvantages all axes have the same origin (zero point) and values are be transformed to the numbers in the 0 – 1 interval according to "the higher is the better" principle. The final polygon area is going to be used as a company score in the same way as Altman did in his original work [5].

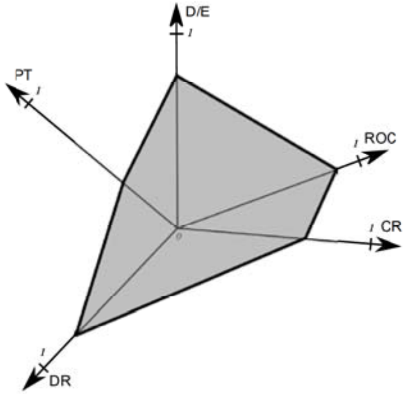

Figure 2: The example of the diagram for the company. The greyed area represents company score. (PT – payables turnover, D/E – debt to equity, ROC – return on costs, CR – current ratio, DR – debt ratio)

The ideal scoring method evaluates each defaulted[1] company[2] by score value lower than any non-defaulted company. This leads to the ordering performance evaluation of the scoring method that is quantified by the Gini and Kolmogorov-Smirnov indexes. The other option is to find out the score threshold value, which means that companies with the score below this value are treated as default and companies with score above this value are treated as non-default companies. Subsequently the true positive rate (sensitivity) and true negative rate (specifity) can be calculated. Threshold value determination is inescapable for default prediction. The difference between this scoring approach and classification models such as logistic regression or neural network is that Gini and Kolmogorov-Smirnov indexes will be used as objective function as well as the measurement of model ordering performance.

Methods used for bankruptcy (failure, default) prediction are based on statistical analysis of subjects' quantitative indicators and information about subjects' failure. The oldest widely used tool for bankruptcy prediction is Altman score [6]. Altman score is the result of discriminant analysis applied on set of companies. The three groups of companies identified based on the score: companies likely to bankrupt, companies unlikely to bankrupt and grey

[1] The definition of defaulted company varies. It can be a company that is not able to fulfil its obligations in specified time (e.g. 90 days) or it is a bankrupted company.

[2] A company is not defaulted in time of evaluation, but gets defaulted during the observation period.

zone where the prediction is not accurate enough. Similar approach is used also for the new proposed method. Score threshold values are defined to separate companies probable to default from other companies. The output of the bankruptcy (failure) prediction is a real number representing score or probability. Score can be in many cases transformed into probability. Logistic regression [7-9] model is very often used for company failure prediction. Logistic regression output represents probability of company default. Other widely used model are neural networks. There are many various neural network models [8, 10-15] (backpropagation neural network, radial basis neural network, support vector machine etc.). Output of these models can be again probability of default. Neural networks and logistic regression are widely used classifiers for company default prediction. In addition, there are other classifiers such as Bayesian models [16-19], decision trees [18, 20, 21], memory based reasoning [14, 18, 22, 23] and evolutionary algorithms [24-26] that can be also used for specified purpose.

Output of all methods is score (or probability), which can be used for performance ordering. This can be also done by benchmarking methods [27-30]. These methods can set up companies order according to specified criterions. New proposed method result is confronted with the benchmarking models results.

The accuracy of models (actually used or new ones) is measured by Gini and Kolmogorov-Smirnov indexes as well as other performance indicators (sensitivity, specificity, etc.) based on hypothesis testing techniques and logic [31-38].

Briefly, actual usage and description of *magic square* was presented. Various classifying methods were also presented and current state of the problematic was elaborated in this section. The new method is interconnecting actual knowledge from classification algorithms (machine learning) with the *magic square* tool and presents new approach that can be used not only as a tool for company failure prediction but also as a benchmarking tool.

2. AIMS OF THE DOCTORAL THESIS

There exist three groups of parameters that affect the polygon area (score).

1. Order of axes. The area of polygon created by more than three indicators depends on the order of axes.
2. Angles between axes. It is not necessary that axes are perpendicular like in figure 1. The only requirement is that sum of all angles must equal to 360°. Polygon area is changing by changing angles between axes.

3. Weight of indicators. Each indicator's value is between 0 – 1. The weight can be any non-negative number by which the indicator value will be multiplied.

The main goal of this work was design a new scoring model. The values of model parameters will be changing in order to achieve highest Gini and Kolmogorov-Smirnov index values. This work will try to find the answer on the following **research questions.**

1. Does axes order have significant impact on Gini and Kolmogorov-Smirnov index values when the weights and angles are constant and equal?
2. Is the performance of proposed scoring method competitive with other methods such as logistic regression or neural networks?
3. Is it necessary to change all groups of parameters or some of them (weights, angles) can remain constant?
4. Is the relative order of electricity distribution companies obtained by proposed method different from assessing by the *Y performance index* used in thesis [28]?

These configurations (scenarios) will be evaluated.

A. Order of the indicators will be determined, other parameters will be constant.
B. The weights will have the identical constant value. Order of the indicators and angles between their axes will be determined.
C. The angles will have the identical constant value. Order of the indicators and their weights will be determined.
D. All of the parameters will be determined (order, weights, angles).

Indicators that enter the calculation are calculated from publicly available data[3]. Proposed method is trained and validated on disjunct datasets. Training in this context means to find out the values of parameters (order, weights and angles) that meet the constraints and achieve maximal Gini (or Kolmogorov-Smirnov) index value. Validation [39] is the process where the values of parameters obtained in training phase are applied on data that are not the part

[3] There is plenty of data sources and information about the companies. Some countries (such as Czech Republic, Slovakia and a few others European countries) have publicly available financial statements of all registered companies free of charge. There is also public insolvency register, debtors register and other free or paid sources. Data gathering differs from country to country and it is dependent on provided data exchange interfaces. This process is time consuming and requires advanced computer knowledge. Due this fact, it is possible to order aggregated data from specialized companies or institutions.

of training dataset. Gini and Kolmogorov-Smirnov indexes values from training and validation phase will be compared. In case when the drop of values between training and validation data sets is not significant[4] one can say that the used method is not fitted just to training data and can be used in general analysis. The results are compared with other widely used methods. Proposed method can be used for relative performance (benchmarking) comparison between companies due the fact that the method output is score, which can be used for construction of relative order. The relative order of performance of electricity distribution companies obtained by proposed method is compared to the order from [28]. Author [28] analysed data using different approach and therefore the comparison has sense.

3. WORKING METHODS

This dissertation is based on utilization of quantitative techniques. Used research procedures are empirical and theoretical. Empirical procedures are processing input data that describe observed objects (companies) and these procedures result in factual conclusions about observed objects. Exact methods on specific data are used to obtain factual knowledge. In addition, theoretical procedures such as deduction are used for drawing conclusions. Historical data that describe companies are used for the models creation. The specific features can be assigned to the research object based on the created model. The common knowledge is applied on individual object and conclusion about this object is made.

Primarily these quantitative methods were used in this dissertation thesis:

- correlation analysis
- descriptive statistics
- statistical modelling
- statistical transformations
- probability sampling

The data used in this work are exact facts about the companies and no subjective inputs (like experts' opinions) were used. These input data were statistically analysed, evaluated and interpreted. Statistical analysis was used for assessment of companies and synthesis is used when final model was developed and when research question were proved or rejected. Finally, comparative methods were used in order to compare results of proposed method with other methods.

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[4] Significance is relative term in this context and the difference in values will be compared with differences in other methods.

Financial ratios (PT – payables turnover, D/E – debt to equity, ROC – return on costs, CR – current ratio, DR – debt ratio) were chosen based on individual performance measured by Gini index and correlation analysis was used to ensure that used ratios are not strongly correlated. Descriptive analysis was used for finding extreme values and replacement of extreme values by reasonable quantile value. Variables were transformed into 0 – 1 interval by application of sigmoid function. Finally, all variables were binned (discretized into categories).

The equation (1) shows calculation of score for individual companies.

$$S = \frac{1}{2}\sum_{i=0}^{N-1} a_i \times a_{(i+1) \bmod N} \times \sin \alpha_i \times w_i \times w_{(i+1) \bmod N} \tag{1}$$

N – vertex count (equal to 5 in this calculation), α_i – angle between consecutive axes
a_i – value on i-th axis, $a_{(i+1) \bmod N}$ – value on axis next to i-th axis,
w_i – weight of the value on i-th axis , $w_{(i+1) \bmod N}$ – weight of the value on axis next to i-th axis

The core idea was to maximize Gini and Kolmogorov-Smirnov indexes values by changing angles, weights and parameters' order. This is the main difference between classifiers and chosen approach, which is actually not a classifier.

$$Gini(\boldsymbol{\alpha}, \boldsymbol{w}, \boldsymbol{o}) \rightarrow MAX \tag{2}$$

$$KS(\boldsymbol{\alpha}, \boldsymbol{w}, \boldsymbol{o}) \rightarrow MAX \tag{3}$$

α – vector of angles, w – vector of weights, o – order vector

Mathemathica software was used to perform maximization process. Numerical methods had to be used due the fact that analytical solution of maximization is practically not possible.

4. RESULTS

The best result for scenario A is Gini index value equal to 29.18 % on validation data. Order of parameter in the best case is [1, 4, 2, 3, 5]. The difference between maximum and minimum values are 1.3 % for Gini index. This is comparable to the best resulting alternative methods.

Impact of parameters' order is slightly higher for KS index than in Gini index optimization. The difference between maximum and minimum values is 2.7 %. The best result for this scenario is KS index value 27.58 % for parameters' order [1, 2, 4, 5, 3].

The best performing settings for scenarios B, C, D are shown in the following table.

ID	Sc.	Order	Weights					Angles				
1	D	1 2 5 3 4	3.7	2.1	3.9	5.5	4.2	40.0	29.4	127.6	64.6	98.4
2	B	1 2 5 3 4	1	1	1	1	1	18.7	8.6	120.8	95.7	116.2
3	C	1 2 5 3 4	6.5	1.8	4.3	9.1	5.3	72	72	72	72	72
4	D	1 4 3 2 5	10.0	9.0	8.0	6.7	0.3	54.3	1.0	69.7	180.0	55.0
5	B	1 3 2 5 4	1	1	1	1	1	106.0	14.7	92.0	116.6	30.7
6	C	1 2 3 4 5	9.1	7.9	7.5	9.1	0.6	72	72	72	72	72

Table 1: The best performing settings of parameters for scenarios B, C, D.

ID	Sc.	Gini Train	Gini Valid.	KS Train	KS Valid.
1	D	0.4148	0.3133		0.2979
2	B	0.4163	**0.3155**	N/A	0.3006
3	C	0.4146	0.3135		0.2841
4	D		0.2938	0.3529	0.2998
5	B	N/A	0.2884	0.3464	0.3028
6	C		0.2863	0.3497	0.3080

Table 2: The first part is the result of Gini maximization and the second part is the result of Kolmogorov-Smirnov index maximization for parameters from table 2.

The results (validation part in the table 2) are close to each other so it is not necessary to search for the values of all three groups of variables (order, weights, angles) and one group can stay constant with the equal values. This is very important for calculation time, which was about several hours up to one day in case of determination of all parameters. The maximization of Gini index leads also to very good[5] results for KS index. This is obvious from the table 2 where KS values are the same in case of Gini maximization and KS maximization – the highest Gini index value on validation data is 31.55 % and KS value is equal to 30.06 % for the same configuration. On the other hand, the maximization of KS index does not lead to the highest possible values of Gini index. The second part of the table 2 shows that Gini index values are 2 – 3 % lower than values obtained by Gini maximization. The highest KS index value from KS index maximization is 30.80 % but corresponding Gini index value is only 28.63 %.

Finally, the configuration with parameters order [1, 2, 5, 3, 4], angles values (18.7°, 8.6°, 120.8°, 95.7°, 116.2°) with all weights equal to one is the best and leads to the result 31.6 % for Gini index value and 30.1 % for KS index value

[5] "Very good" is a term of wide comprehension. Gini and KS indexes values around 30 % on validation dataset are the best values achieved on given data even when using alternative methods. Values similar to these ones are considered as very good.

on validation data. The aim was to choose one result for proposed method. The configuration with the highest Gini index value was chosen because also KS index value is very good (not the best, but higher than 30 %). On the other hand, if the configuration with highest KS index value was chosen, corresponding Gini index value would be lower by 3 % from the best case which is not optimal. This was a kind of multi-criterial decision where both criterions were assumed and the aim was to have the maximum value of one indicator and reasonable value of another indicator. Aim was fulfilled and the results were presented.

Equation (4) shows the final score calculation. Variables entering the formula are the transformed weight of evidence values, not the original financial ratios. For proper score usage, the original values have to be transformed onto weight of evidence values and consequently transformed. The constant in each term represents sine of corresponding angle. This is due the fact, that weights are equal to one. Otherwise, also the weights should be included into the calculation.

$$Score = \frac{1}{2} \times (0.321 \times PT \times DOE + 0.15 \times DOE \times DR + 0.897 \times DR \times ROC + 0.859 \times ROC \times CR + 0.995 \times CR \times PT) \quad (4)$$

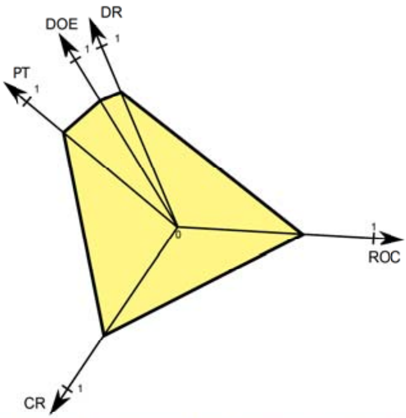

Figure 3: The pentagon diagram of the best rated company (score = 0.82).

Figures 3 and 4 show the polygon (pentagon) diagram for the best and the worst rated company from validation data set. One can notice only a small angle between DOE and DR axes. These two indicators are from the same group of indicators and therefore reduction of one of them should be considered. This can be also a way how maximization procedure can reduce unnecessary variables.

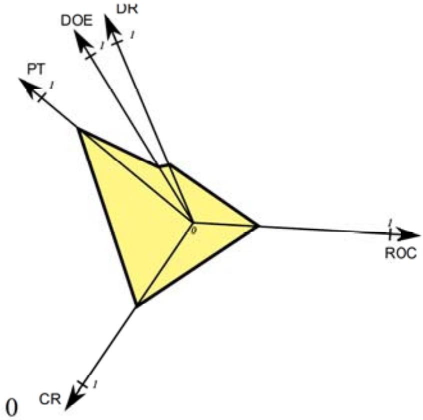

Figure 4: Pentagon diagram of the worst rated company (score = 0.2)

Based on newly discovered information the DOE indicator was removed the angle between PT and DR indicator was set to the sum of angles between PT and DOE and DR axes. The new configuration order is [1, 4, 2, 3], angles values (27.3°, 120.8°, 95.7°, 116.2°) with all weights equal to one. The Gini and Kolmogorov-Smirnov indexes are equal to 31.25 % and 28.53 % respectively on validation data set. The values for quadrangle are practically the same for Gini index value and slightly lower (by 1.5 %) for KS index value. These results are still very good and competitive to alternative methods with the best results. The big advantage is that performance is preserved even with reduction of one parameter.

Equation (5) shows simplified score calculation where DOE parameter is omitted. The other calculation logic is the same as for formula (4).

$$Score = \frac{1}{2} \times (0.459 \times PT \times DR + 0.897 \times DR \times ROC \times 0.897 + 0.859 \times ROC \times CR + 0.995 \times CR \times PT) \qquad (5)$$

Following tables show comparison between ordering performance of the new proposed method with the methods where calculation was performed by SAS software. Radial basis neural network with three hidden neurons performs best on training dataset in both Gini and KS indexes calculations. Despite of these excellent training results, the performance on validation dataset dramatically falls below the performance even of methods that had lower training score.

Method	Gini Train	Gini Validation
Proposed (Scenario B)	0.416	0.312
Altman	N/A	0.207
Logistic Regression	0.420	0.301
Neural Network (Back Propagation 3H)	0.454	0.291
Neural Network (Radial Basis 3H)	0.508	0.265
Memory Based Reasoning (K-Nearest Neighbours)	0.422	0.199

Table 3: Comparison of proposed method with other methods – Gini index

Method	KS Train	KS Validation
Proposed (Scenario B)	N/A[6]	0.301
Altman	N/A	0.248
Logistic Regression	0.317	0.299
Neural Network (Back Propagation 3H)	0.337	0.292
Neural Network (Radial Basis 3H)	0.412	0.225
Memory Based Reasoning (K-Nearest Neighbours)	0.340	0.216

Table 4: Comparison of proposed method with other methods – KS index

The big difference between training and training stage can be caused by overfitting where model is well adopted to training data, but performance on validation data is poor. From the result tables 3 – 7 it is obvious that the best (highest) values of Gini and KS indexes are around 30 % on validation dataset. Logistic regression, neural networks are used in the most cases for company failure prediction and the results show that this is legitimate because performance indicators for these methods are among the best results. From the other classification algorithms used in machine learning the linear Bayes classifier and grammatical evolution belong also to the group of the best performing methods.

[6] The results of proposed method for the best scenario B (table 2). Train value is not relevant because optimization was performed on Gini index and the KS value was calculated on validation dataset.

Method	Gini Train	Gini Validation
Linear perceptron	0.2507	0.1621
Neural Network (Back Propagation 2H)	0.3907	0.3076
Neural Network (Radial Basis 2H)	0.7552	0.2032
Neural Net (Levenberg–Marquardt)	0.4129	0.3017
Support Vector Machine	0.3566	0.2594
Naive Bayes	0.4185	0.2869
Linear Bayes	0.4192	0.3043
Adaptive Boosting	0.3989	0.2681
Quadratic Bayes	0.4330	0.2702
Mixture of Gaussian and Bayes	0.4625	0.2316
C4.5 Decision Tree	0.2712	0.2036
Random Forest	0.3043	0.2020
Scaled Nearest Mean	0.4008	0.2853

Table 5: Comparison with other classification methods – Gini index

Method	KS Train	KS Validation
Linear perceptron	0.0065	0.0314
Neural Network (Back Propagation 2H)	0.3072	0.2644
Neural Network (Radial Basis 2H)	0.5392	0.2043
Neural Net (Levenberg–Marquardt)	0.3203	0.3084
Support Vector Machine	0.3203	0.2579
Naive Bayes	0.3268	0.2706
Linear Bayes	0.3333	0.3069
Adaptive Boosting	0.3301	0.2979
Quadratic Bayes	0.3366	0.2835
Mixture of Gaussian and Bayes	0.3464	0.2855
C4.5 Decision Tree	0.2810	0.2537
Random Forest	0.2908	0.1919
Scaled Nearest Mean	0.3333	0.2658

Table 6: Comparison with other classification methods – KS index

A brief comparison of other results achieved by Matlab software is shown in tables 5 and 6. It is noticeable that radial basis neural network with two hidden neurons has perfect results on training data but performance on validation dataset is much worse in comparison to training dataset and also to other methods. The methods based on Bayesian classifier are well performing with exception of mixed Gaussian and Bayes classifier where dramatic drop between training and validation dataset is present. The nearest mean algorithm, which belongs to memory based reasoning algorithms, is also well performing.

The best results for grammatical evolution were achieved by maximizing Gini index. The KS index maximization resulted lower performance for both Gini and KS values similarly to proposed method where this behaviour was also present. The median values from all runs are presented in the following table.

Method	Gini Train	Gini Validation	KS Train	KS Validation
Grammatical evolution	0.4035	0.3023	0.3148	0.2869

Table 7: The results for grammatical evolution

From this comparison, it is obvious that proposed method performance is competitive to other methods. The decision trees methods are least performing, their Gini index values are around 20 % and these methods do not look suitable for company failure prediction based on given data. Other methods are usable. There is at least one method within each group with very good results. For example, backpropagation neural networks are the best performing from the neural networks group, linear Bayes classifier is the best performing from Bayesian models group, scaled nearest mean has also good results and belongs to memory based reasoning algorithms. Grammatical evolution and logistic regression have also excellent results.

Proposed method can be also used for the relative comparison of companies' performance because the method gives a score and not the only Boolean information whether company will default or not. The score is calculated based on financial statements data and information about company failure in the meaning of ability to fulfil obligations. The simple assumption is that companies that are able to fulfil their obligations are well performing and companies that are not able to fulfil their obligations are bad performing. In other words high score does not only mean that a company is less probable to default, but also means that a company's core business is healthy and a company performs well in its business area. This idea can be used for the comparison of several companies, in this case electricity distribution companies.

Several distribution companies were chosen for comparison. It is subset of companies used in doctoral thesis [28].

Distributor	Score	Score4	Y	CRS	VRS	MBM
AEW	0,70	0,70	142,62	100,00	100,00	89,62
SPD	0,44	0,44	86,46	100,00	100,00	89,50
RARIK	0,43	0,40	67,93	46,35	89,98	71,78
NPG	0,36	0,35	61,90	100,00	100,00	80,68
CEZ BG	0,53	0,51	51,30	50,64	100,00	67,62
ADGER	0,34	0,35	45,72	29,01	33,57	73,73
EON	0,48	0,46	42,53	21,75	35,62	66,25
SRD	0,51	0,51	38,48	66,45	77,18	71,88
ENW	0,42	0,42	35,29	30,93	100,00	73,37
SADALES	0,40	0,39	9,44	7,37	40,51	61,04
HEP	0,33	0,29	16,63	8,07	37,40	57,77
EESTI	0,35	0,34	20,29	7,67	32,52	62,98
CEZ CZ	0,57	0,57	29,66	13,43	34,29	66,01
EM	0,60	0,58	20,71	12,15	37,77	65,07

Table 8: Scores of various methods used for comparison

The table 8 shows the result of application of proposed method and benchmarking methods from doctoral thesis [28] on selected distribution companies. The column "Score" is the result of proposed method and "Score4" is the result of modified proposed method where only four input parameters were used. The difference in results between five and four used parameters is small and therefore the modification with four parameters can be used without a significant impact on final score. The "Y" column represents "Y" performance index, CRS represent constant return to scale (CCR) model, VRS is the variable return to scale model (BCC) and MBM is represents referential point method.

The table 9 represents the differences in relative performance order between proposed method and benchmarking methods from [28].

Distributor	Y	CRS	VRS	MBM
AEW	1	1	1	1
EM	3	3	3	3
CEZ CZ	3	3	3	3
CEZ BG	1	1	1	2
SRD	1	1	1	1
EON	1	1	2	1
SPD	2	2	2	2
ENW	1	1	2	1
RARIK	2	1	1	1
SADALES	2	2	1	1
NPG	3	3	3	3
ADGER	2	2	1	3
EESTI	1	1	1	1
HEP	1	1	2	1

Table 9: Differences between proposed method and benchmarking methods

The differences were divided into three groups that represent the difference in order of proposed method and method in column heading.

- Group 1 (green): the order difference is between 0 and 3.
- Group 2 (orange): the order difference is between 4 and 6.
- Group 3 (red): the order difference is between 7 and 9.

It is noticeable that the proposed method assesses distribution companies very similarly in a half of cases. Seven or eight companies belong to the first group, which means that the difference in assessment between proposed method and benchmarking models is low. Approximately quarter of cases belongs to the second group, which means the considerable difference between proposed and benchmarking models and finally in the quarter of cases the difference is big.

Differences between proposed method and methods from [28] are caused by different input parameters and different data on which methods were trained on. One cannot say which method is better in general, but methods developed on data from power distribution companies should have higher performance for power distribution companies' assessment. On the other hand, their usage is limited to power distributors and cannot be used for any company as the proposed method can. Nevertheless, proposed method performed well for power distribution companies that can be considered as very specific kind of data.

5. CONCLUSION

The aim of this thesis was to propose a new scoring method for companies' default prediction. The proposed method is based on *magic square* concept that is used in macroeconomic evaluation of individual countries. Concept of *magic square* was extended to general polygon with many possible settings. Input variables represented by companies' financial ratios were transformed to achieve desired properties (better variable value is located further on axis than worse value). Therefore, area of polygon can represent score for particular company.

The core of proposed method development was in changing of parameters (weights, angles, axes order) in order to maximize the value of Gini and Kolmogorov-Smirnov indexes. Consequently comprehensive performance comparison was performed and method was used also for benchmarking purposes.

Proposed method is not a standard classifier but it can be used in the very similar way as the classification algorithms. The performance of the proposed method is comparable to logistic regression, various neural networks models, Bayes classifiers, evolutionary algorithms etc. Both Gini and KS indexes values are around 30 % on validation data set for the methods with the highest performance. This number is not high and it is lower than expected in real scoring models. This is caused by the fact that data quality is not ideal and deep data pre-processing was not the aim of this paper. The important is that the new proposed method is as good as competitive methods applied for required classification task. Indisputable advantage of proposed method is in visualisation that was inspired by the magic square, which is often used in comparison between economies of different countries. The result of company scoring is not the only number but also a diagram, which shows strength of individual factors influencing the final score and overall performance.

Proposed method output score can be also used for relative companies' performance comparison. This comparison was performed for 14 electricity distribution companies. The results were compared to the benchmarking methods results, especially to the new benchmarking method designed in doctoral thesis, which was dealing with the problematics of benchmarking models. The comparison of proposed method and new benchmarking method was done as the result of research cooperation at the Czech Technical University in Prague. Results show that proposed method can be also used for benchmarking under limited conditions. Results are good with respect to that fact that proposed method was developed on the companies from all economic sectors and the benchmarking was done on a specific industrial sector (electricity distribution companies).

The advantage of proposed method is that it is universal. It can be used for default prediction, credit scoring and for benchmarking purposes. Another advantage is in simple visualisation, which is indisputable benefit for users.

Answers on research questions:

Does axes order have significant impact on Gini and Kolmogorov-Smirnov index values when the weights and angles are constant and equal?

Parameters order does not have significant impact on Gini index in case of constant weights and angles. Kolmogorov-Smirnov index is more sensitive on axes order than Gini index and its value is affected by parameters order on the above-mentioned assumptions.

The situation can change (impact can be significant) in case of extreme angles values and weight values. Significance falls with growing number of input parameters due the fact that polygon area is divided into more triangles and relative impact of one parameter is smaller than in case of low number of input parameters.

Is the performance of proposed scoring method competitive with other methods such as logistic regression or neural networks?

Yes, the performance of proposed method is competitive with other methods used for company scoring. Results show that the performance of proposed method belongs to the group of methods with the highest performance.

Is it necessary to change all groups of parameters or some of them (weights, angles) can remain constant?

No, the results show that the highest Gini and Kolmogorov-Smirnov indexes can be achieved when angles or weights are constant. The result with constant weights was selected as the best one.

Models with constant weights along with constant angles have lower performance than models with constant only one group of these parameters.

Is the relative order of electricity distribution companies obtained by proposed method different from assessing by the Y performance index used in dissertation thesis [6] ?

The relative order of electricity distribution companies by proposed method differs from the Y performance index results. There is significant group of distribution companies that were assessed similarly by the both methods, but assessment of the whole sample was not the same and therefore this research question cannot be answered positively.

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Authors' shares: Bemš 65 %, Macaš 10 %, Pošík 5 %, Žegklitz 10 %, Starý 10 %.

Publications in reviewed journals

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SUMMARY

This dissertation thesis introduces the new scoring method for company default prediction that can be also used as a benchmarking tool for relative performance comparison of companies. The method is based on usage of the modified *magic square* (spider diagram with four perpendicular axes) which is used to evaluate economic performance of a country. Evaluation is quantified by the area of quadrangle, which vertexes are points lying on the axes. This new method deals with magic square shortcomings e.g. axis zero point not in the axes origins. The idea of quadrangle is extended to polygon. The polygon area represents the company score. The main goal is to find out the parameters such as axes order, parameters weights and angles between axes in the way to achieve best scoring performance.

Input data are financial ratios from financial statements (debt ratio, return on costs etc.) and information about company default (or bankruptcy). The aim was to achieve good ordering performance (defaulted companies should have lower score than non-defaulted companies) which is represented by Gini and Kolmogorov-Smirnov indexes. In addition, threshold value for score dividing default and non-default companies was calculated because it is necessary for default prediction, true positive rate and true negative rate calculation. Training and validation processes were performed on two independent and disjunct datasets.

Results show that performance of this new method is comparable to other methods such as logistic regression and neural networks. Moreover, the number of parameter groups can be reduced without negative impact on the performance. Proposed method was also used for performance comparison of power distribution companies. Results were also compared to specialized benchmarking methods used for assessment of companies in power distribution sector.

The real advantage over other methods is in graphical representation in diagram and its universality because it can be used for companies' failure prediction and as a benchmarking tool.

RÉSUMÉ

Tato dizertační práce přináší novou hodnotící metodu, která může být použita zejména pro predikci neschopnosti firem plnit své závazky. Tento přístup může být rovněž použit jako nástroj pro relativní srovnání výkonnosti firem. Metoda je založena na *magickém čtyřúhelníku* (pavučinový diagram se čtyřmi kolmými osami), který se používá pro hodnocení výkonnosti ekonomiky. Plocha čtyřúhelníku, která je tvořena údaji na osách je použita jako měřítko výkonnosti. Navrhována metoda odstraňuje nedostatky magického čtyřúhelníku jako např. že bod nula neleží na průsečíku os. Myšlenka čtyřúhelníku je rozšířená na mnohoúhelník, kterého obsah vyjadřuje skóre. Hlavním cílem je najít parametry jako pořadí os, váhy jednotlivých parametrů a úhly mezi osami tak, aby byla dosažena nejlepší výkonnost v hodnocení firem.

Vstupní data jsou poměrové finanční ukazatele z finančních výkazů (zadluženost, výnosy na jednotku nákladů atd.) a informace zdali společnost byla schopna splácet své závazky (nebo zkrachovala). Cílem bylo dosáhnout dobrou výkonnost v řazení firem (firmy s finančními problémy by měly mít nižší skóre než zdravé firmy), která je měřena Gini indexem a Kolmogorov-Smirnovým indexem. Navíc byla stanovena mezní hodnota skóre, která odděluje problémové společnosti od ostatních. Tato hodnota je potřebná pro určení procenta správně předikovaných společností pomocí uvedené metody. Proces trénování a validace byl proveden na dvou nezávislých oddělených datových souborech.

Výsledky ukazují, že výkonnost navrhované metody je srovnatelná s metodami jako logistická regrese a neuronové sítě. Navíc pro zachování velmi dobrých výsledků není potřebné použít všechny skupiny parametrů. Navrhovaná metoda byla taktéž použita pro srovnání výkonnosti společností působících v sektoru distribuce elektřiny. Její výsledky byly srovnány se specializovanými metodami, které se používají pro distribuční společnosti.

Velikou výhodou této metody oproti jiným metodám je její snadná grafická reprezentace v diagramu. Další výhodou je její univerzálnost protože může být použita pro předpověď finančních potíži a taktéž jako nástroj pro srovnání výkonnosti.