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Scoring Models: towards the More Realistic Approach

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Abstract: Financial decision-making is one of the most current issues of modern financial management. Financial decision-making is an area where decision support systems, knowledge-based decision support systems, and intelligent decision support systems are successfully applied. In consequence of the importance and complexity of this problem area a large number of methods of support to financial decision-making was developed. This paper presents the most important features of two decision support systems, a classical system and a system based on fuzzy logic. The performances of these two models are compared and the advantages achieved through the introduction of fuzzy concepts into the classical decision support systems are determined.

Key words: decision-making, decision support systems, fuzzy logic.

1. Introduction

Financial decision-making is one of the most current issues of modern financial management. From the point of view of banking system, one of the most relevant problems of financial decision-making is certainly a decision whether to grant a credit to a business or not. The importance and complexity of this problem area are the reasons why methods have been developed over the years to treat this issue in the most realistic manner. The need for appropriate and effective methods and procedures is justified by very high complexity of the actual situation, making it more difficult to fit into restrictive hypotheses that mathematical models rely on more often than not.

Decision support systems, knowledge based decision support systems, as well as intelligent decision support systems, can be applied in a wide spectrum of real problems, for greater details see [2] and [3]. This problem of financial decision-making was first solved by means of a classical decision support system. The advantage of this approach lies in the fact that it is clearly mathematically defined, but its deficiency is the lack of consistency in representing the real situation. Modifications of the classical approach were done in various directions. All those modifications were made with an aim to make models closer to real situation and to take into consideration real conditions and restrictions. In some cases values of observed indicators, i.e. criteria, are characterised by imprecision and uncertainty. A basic limitation of the classical model is seen in the fact that criteria values are rigidly comprehended, i.e. two alternatives (credit applications) will be considered equal in terms of one criterion only if its values are identical, and in case of a small change in the value one of the alternatives will be considered a better one, which does not correspond to the real situation where preferences are not always so strict. All of the above has resulted in the change of our understanding of financial decision-making models. By applying fuzzy logic in decision support systems we obtain models that can be successfully applied in the field of financial decision-making since they realistically model the facts and relationships that characterise the reality.

The scope of research in this paper is to compare two financial decision support systems – the classical system and the system based on fuzzy logic. Also, in terms of a scientific contribution this paper is expected to improve the existing methodology in support of financial decision-making process by introducing certain improvements into existing systems applicable in the real banking environment.

2. Financial decision support system

This chapter presents a modelling proposal how to arrive at a financial decision. This analysis treats the issue of taking a decision to grant credit to a certain business. This model will assign a certain score to a business that files a credit application with the bank. Based on the score, the decision-maker, in this case the bank, will decide whether to grant credit or not.

Relevant data for a given client may be grouped into several groups. The following data groups can be observed, for example:

- Financial data
- Non-financial data
- Qualitative data

A partial score is calculated for each data group. The total score is obtained by applying relevant weights on partial scores. The resulting total score is then used in the process of making credit decision. As the modelling principle is the same for each of the above groups and for final score, we will present only the following models:

- Classical approach: models for the calculation of client's financial and qualitative score
- Fuzzy approach: model for the calculation of client's financial score

It is worth noting that all specific weights of indicators used in this model are set by a relevant bank department (credit risk department) together with the management of the bank, in accordance with the pre-defined credit policy of the bank. This is important to know since the specific weights can have a significant impact on the final score of a business, and consequently on the final financial decision. Also, the bank defines all other relevant parameters necessary for calculating the score and implementing the decision-making process. In the next two chapters (2.1. and 2.2.) models for the calculation of client's financial and qualitative score will be presented.

2.1. Financial score

Financial data used in determining financial score of a business are shown in Figure 1, for more details on financial indicators see [4]. The model for calculating business' score is based on determining possible value ranges for each indicator and then each range is assigned a relevant score. Thus, if the relevant indicator value fits into a certain range then such indicator is assigned its pre-defined score. The total score is obtained as a weighted sum of scores of all indicators. Each of the indicators is assigned a weight.

The table 1 shows ranges of possible indicator values and corresponding scores. These values are set by the bank depending upon its preferences and internal credit policy. The Table 2 shows financial indicator values for a business that is taken as a realistic example, and Table 3 shows scores that were assigned to each of the indicator values based on the presented model.

Note: Defined value ranges cover minimum value, but do not cover maximum value. Thus, for *the debt to equity ratio* of 1.5, the business will be assigned score of 25.

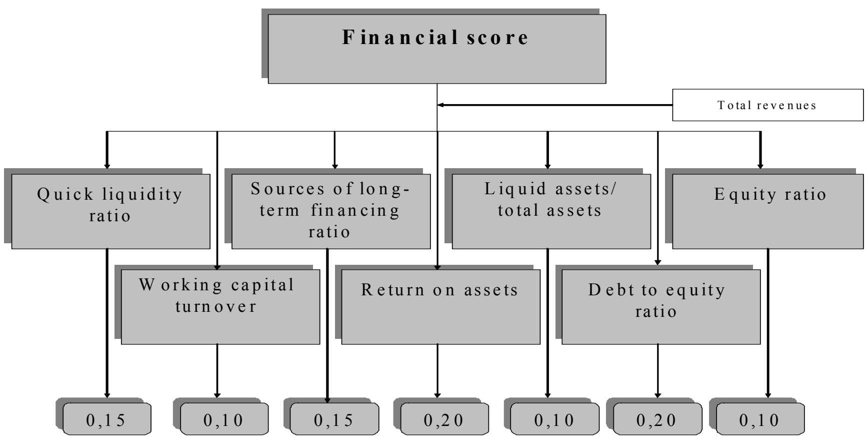


Fig. 1. Financial indicators and their weights

Table 1. Value ranges of financial indicators

Quick liquidity ratio		
Minimum value	*Maximum value*	*Score*
0	0.4	0
0.4	0.7	25
0.7	1.0	50
1.0	-	100

Sources of long-term financing ratio		
Minimum value	*Maximum value*	*Score*
-	0	0
0	0.2	25
0.2	0.4	50
0.4	0.5	75
0.5	1	100

Liquid assets (cash + equivalents) / total assets		
Minimum value	*Maximum value*	*Score*
0%	10%	0
10%	30%	25
30%	40%	50
40%	100%	100

Equity ratio		
Minimum value	*Maximum value*	*Score*
0%	20%	0
20%	40%	25
40%	60%	50
60%	80%	75
80%	100%	100

Working capital turnover		
Minimum value	*Maximum value*	*Score*
0	0,5	0
0,5	1	25
1	3	75
3	-	100

Return on assets		
Minimum value	*Maximum value*	*Score*
-	0	0
0	25%	25
25%	50%	50
50%	-	100
0,5	1	100

Debt to equity ratio		
Minimum value	*Maximum value*	*Score*
-	0	0
0	0.5	100
0.5	1	75
1	1.5	50
1.5	3	25
3	-	0

Table 2. Values of financial indicators for the real example

Indicators	31 Dec. 2002	31 Dec. 2003	31 Dec. 2004	31 Dec. 2005
Quick liquidity ratio	0.63	0.51	0.51	0.68
Sources of long-term financing ratio	0.40	0.31	0.33	0.49
Liquid assets (cash + equivalents) / total assets %	25.16	23.56	22.53	24.57
Equity ratio %	45.89	49.82	56.01	63.85
Working capital turnover	3.15	3.64	3.64	2.70
Return on assets	26.88	36.40	29.42	38.06
Debt to equity ratio	2.28	1.36	1.54	0.84

The Table 3 shows scores assigned to each value of the financial indicators from Table 1. The last row in this table shows financial score of the business. As the scores may range from 0 to 100, one could say that the financial score of the business at hand has been quite well balanced over the four years, and that the best score was obtained for the last year analysed. The final decision on whether the resulted score can be accepted may be reached by comparing the score with a pre-defined reference value. For example, the score will be deemed acceptable if it is greater than 80, in case of a rigorous approach, or if greater than 30 in case of a flexible approach. Also, it can be left for the decision-maker to assess if the obtained score is acceptable or not.

Table 3. Indicator scores and financial score

Indicators	31 Dec. 2002	31 Dec. 2003	31 Dec. 2004	31 Dec. 2005	Weights
Quick liquidity ratio	25	25	25	25	**0.15**
Sources of long-term financing ratio	75	50	50	75	**0.15**
Liquid assets (cash + equivalents) / total assets	25	25	25	25	**0.1**

Equity ratio %	50	50	50	75	**0.1**
Working capital turnover	100	100	100	75	**0.1**
Return on assets	50	50	50	50	**0.2**
Debt to equity ratio	25	50	25	75	**0.2**
Financial score	**47.5**	**48.75**	**43.75**	**57.5**	

2.2. Qualitative score

Qualitative indicators used to determine qualitative partial score of a client are shown in figure 2.

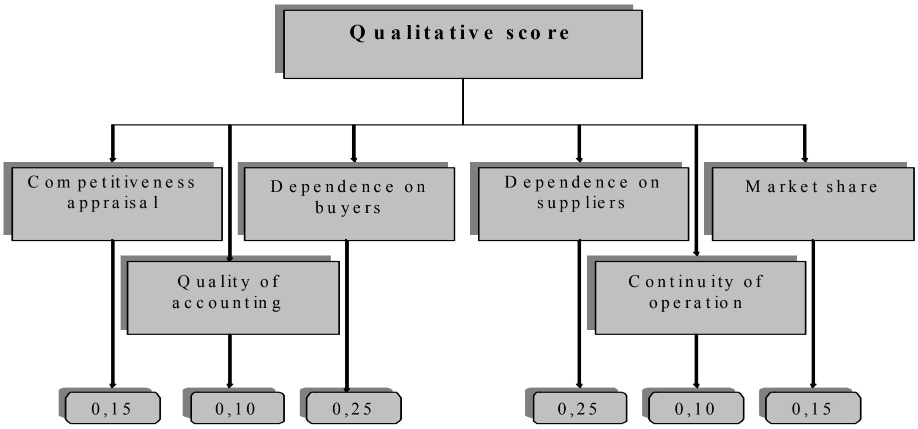


Fig.2. Qualitative indicators and their weights

The model of calculating qualitative partial score is identical to that shown in the section 2.1.

Table 4 shows the ranges of possible parameter values and the corresponding scores, all set by the bank. The calculation of a qualitative score of the given business is shown in Tables 5 and 6. Table 5 shows the values of qualitative indicators and Table 6 shows scores assigned to each of the indicator values based on the presented model. Qualitative score of a client is calculated as a weighted sum of all indicator scores.

Note: Information about the broader social aspects of the investment may also be regarded as qualitative data. They are indicators, such as investment's impact on employment, impact on modernization of technology, impact on environment protection, and the like.

Table 4. Value ranges of qualitative indicators

Competitiveness appraisal	
Value	*Score*
More competitive	100
Equally competitive	50
Uncompetitive	0
No information available	0

Dependence on buyers	
Value	*Score*
High	0
Average	50
Low	100

Dependence on suppliers	
Value	*Score*
High	0
Average	50
Low	100

Market share	
Value	*Score*
Decreasing	0
Stable	50
Increasing	100
No information	0

Quality of accounting	
Value	*Score*
Good	100
Medium	50
Poor	0

Continuity of operation	
Value	*Score*
Not ensured	0
Ensured	100
No information	0

Table 5. Qualitative indicators of the given business

Indicators	**Value**
Competitiveness appraisal	Equally competitive
Dependence on buyers	Average
Dependence on suppliers	Average
Market share	Increasing
Quality of accounting	Good
Continuity of operation	Ensured

The meanings of qualitative indicators stated in this section are less obvious and call for certain explanations.

The competitiveness-assessing indicator compares the position of the given business with that of its market competitors. As many aspects of comparison as possible should be taken into account, for example range of products, market competence, marketing development rate, new product development, location, and others.

Table 6. Indicator scores and qualitative score of the given business

Indicators	Score	Weight
Competitiveness appraisal	50	**0.15**
Dependence on buyers	50	**0.25**
Dependence on suppliers	50	**0.25**
Market share	100	**0.15**
Quality of accounting	100	**0.1**
Continuity of operation	100	**0.1**
Qualitative Score	**67.5**	

The two extreme values of the dependence on buyers indicator are:

- High dependence, meaning that a small number of buyers accounts for a very high percentage of the overall sales of the given business;
- Low dependence, meaning that there are no buyers with particularly high share in the overall sales of the given business.

Similarly, two extreme values of the dependence on suppliers indicator are:

- High dependence, meaning that a small number of suppliers accounts for a very high percentage of the overall procurement in the given business;
- Low dependence, meaning that there are no dominant suppliers, and that the suppliers are easily replaced.

The market share is determined based on the growth rate of the market whereon a business operates. Thus, market is decreasing if the market growth is less than -2 %, market is believed to be stable if the market growth ranges from +2% to -2%, and market is increasing if the market growth exceeds 2 %. The quality of accounting is good if all required financial statements are available completely and in a short time, and it is bad if key financial indicators are unknown.

The indicator of continuity of operation points to whether there is a substitute for or an heir of the business owner who could maintain smooth operation of the business in case the owner becomes unable to discharge his or her duties. In case there is no such substitute, that could be a potential risk to continuity of unhindered operation.

3. Fuzzy system for financial decision support

This chapter presents a model of support to the intelligent financial decision making process, which is accomplished through a fuzzy expert system. The fuzzy approach is very suitable for expert knowledge modelling in various fields, amongst which is the field of financial analysis. The main reason for the application of fuzzy approach is the very nature of the problem. Determination of financial standing and business success of a business does not have a discrete but, like most other real problems, a continuous character.

The imperfection of the classical approach is that small changes of input data may result in a completely different outcome, which in this case would mean a different assessment of a business and a different credit decision. Such sensitivity of output result to the change of input values is typical of the models based on discrete, non-fuzzy approach.

Introduction of fuzzy sets for each given indicator, reflecting the cognitive state of facts, results in a more flexible and a more realistic system of knowledge presentation. Each of input variables will be treated as one linguistic variable. Several values, i.e. attributes, will be allocated to each linguistic variable. The fuzzy model of financial decision-making is presented in a few interconnected steps:

- Definition of basic parameters of the model (number of input and output variables, definition of basic logical operations),
- Definition of a set of attributes for each input and output variable,
- Definition of a set of rules for calculating the value of the output variable,
- Interpretation of results.

Table 7. Financial variables and their attributes

Financial indicators		
Input variables		
Variable	**Indicator**	**Attributes**
fi1	Quick liquidity ratio	Satisfactory Unsatisfactory
fi2	Sources of long-term financing ratio	Satisfactory Unsatisfactory
fi3	Liquid assets/total assets %	Satisfactory Unsatisfactory

fi4	Equity ratio %	Satisfactory Unsatisfactory
fi5	Working capital turnover	Satisfactory Unsatisfactory
fi6	Return on assets	Satisfactory Relatively_Satisfactory Unsatisfactory
fi7	Debt to equity ratio	Satisfactory Relatively_Satisfactory Unsatisfactory
Output variable		
fi	Financial score	Satisfactory Relatively_Satisfactory Unsatisfactory

The application of this model results in the evaluation of the financial standing and successfulness of business operation. This output variable is called the financial score. Table 7 shows the output and all input financial variables and attributes assigned to them. Figure 3 shows the stated variables with the help of classical and fuzzy sets. Visual comparison of these two types of sets – classical and fuzzy – may give us an intuitive impression of the difference between the two modelling approaches.

The fuzzy model of financial decision-making is implemented using MatLab software package, version 6.5. MatLab is software designed for solving a wide range of mathematical problems. Among other things, a part of MatLab is dedicated to operations with fuzzy sets. It is that part of MatLab, the so-called *fuzzy toolbox* that is used in this paper to solve decision making problems.

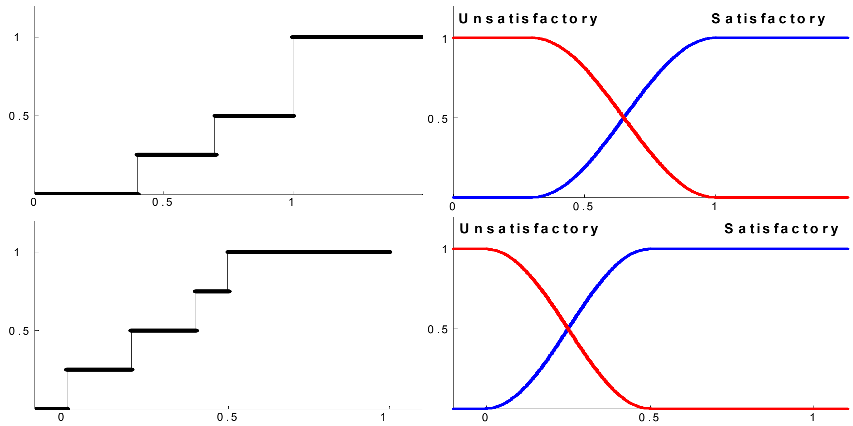
Table 8. Transformation of input variables

Variable	Transformation
fi1	fi1>1.5 → fi1 = 1.5
fi2	fi2<-0.1 → fi2 = -0.1
fi5	fi5>4 → fi5 = 4
fi6	fi6<-5 → fi6 = -5 fi6>60 → fi6 = 60
fi7	fi7>3.5 → fi7 = 3.5 fi7< 0 → fi7 = 3.5

Note: It is necessary to introduce certain transformations (Table 8) for certain input variables so as to reduce their domain to a finite interval. These transformations do not affect the accuracy of the data. Also, the transformation introduced for the *fi7* variable simplifies the form of attributes and reduces them to a form closer to the intuitive impression.

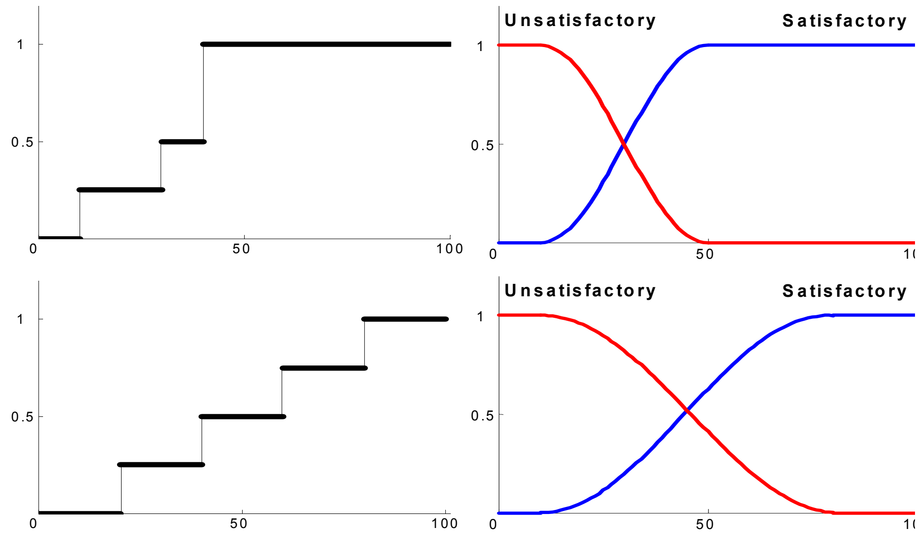
Thus defined financial indicators (variables), as well as the relations among them (inference rules), form the fuzzy model of financial decision-making. The inference mechanism in the MatLab fuzzy toolbox operates on the basis of fuzzy decision-making and fuzzy reasoning. Thus, on the basis of **input variables** and **inference rules,** we get the value of **output variable.**

Quick liquidity ratio



Liquid assets/Total assets

Sources of long-term financing ratio



Working capital turnover

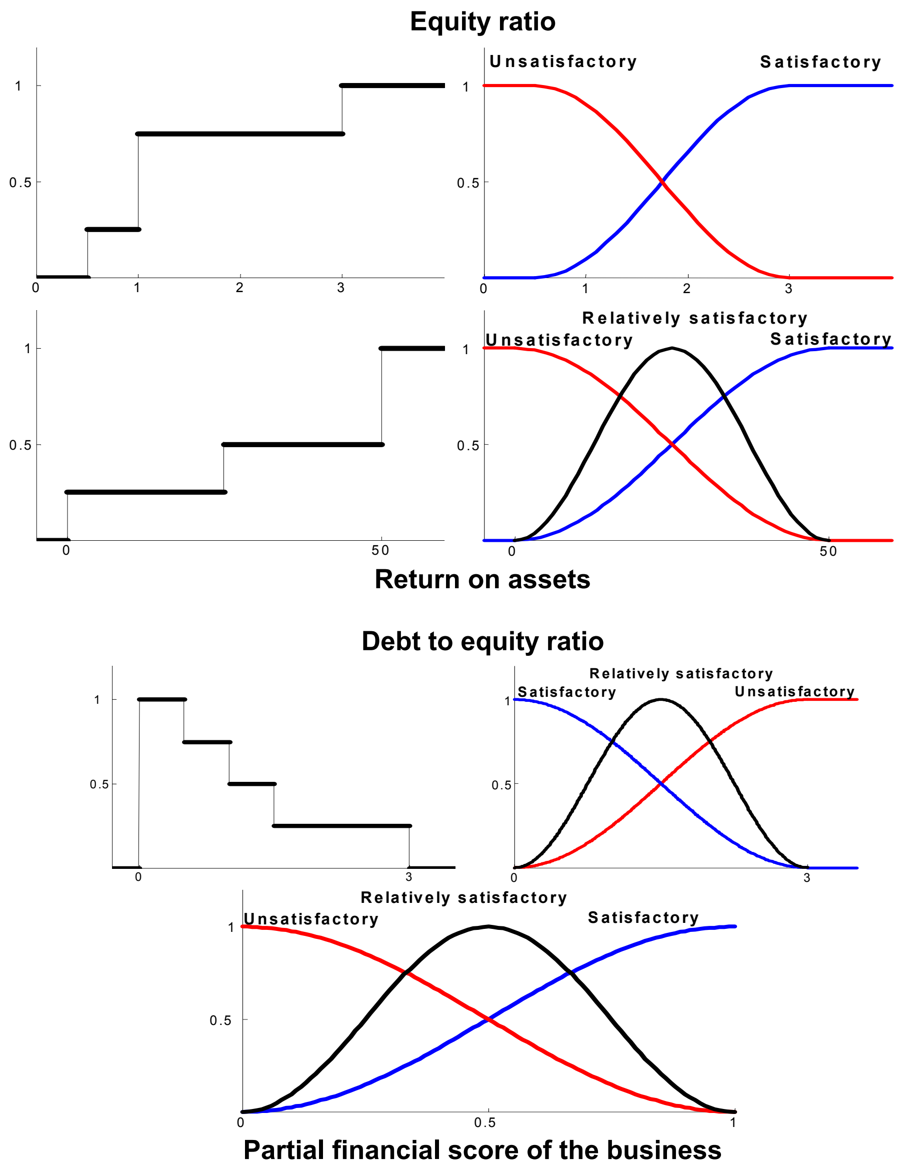


Fig. 3. Classical and fuzzy sets – financial variables

Implementation of the fuzzy model involves the following steps:

a) Definition of basic parameters of the model

We should first define the number of input and output variables and their names. We also need to define logical operations to be applied in the process of decision making, in particular the following operations:

- *and*

- *or*
- *implication*
- *aggregation*

MatLab offers several options to define these operations. The author of this paper has opted for the following standard interpretation of these operations:

- Operations *and, implication* are represented by *min method*
- Operations *or, aggregation* are represented by *max method.*

It is also necessary to select one of the several offered methods of defuzzification. We have opted here for the *lom (largest of maximum) method.*

b) Definition of attributes for all variables

Attributes, i.e. the domain and form of attributes, are defined for all variables in the model. Each attribute is represented by one fuzzy set. Various forms of fuzzy sets may be used, such as trapezoid sets, different forms of Gaussian curves, S-curves and similar. The forms of fuzzy sets chosen to be used in this paper are S-curves and Gaussian curves. These forms represent the meaning of specific variables in a simple and effective manner. The domains of fuzzy sets are specified by the very definition of each of the linguistic variables.

c) Definition of inference rules

The inference rules are defined in the form of *if-then* statement. These rules are defined by the user in line with user's own needs and preferences. Let us adopt the following inference rules on the basis of which it is possible to calculate a financial score of a business:

- If the value of at least any two input variables is *Unsatisfactory,* then the value of the output variable is *Unsatisfactory;*
- If the value of all input variables is *Satisfactory* or *Relatively satisfactory* then the value of the output variable is *Relatively satisfactory;*
- If the value of all input variables is strictly *Satisfactory* then the value of the output variable is *Satisfactory.*

d) Interpretation of results

The three previously described steps have been used to complete the definition of the fuzzy model of calculating the financial score of the business. The next step is to interpret the results. In the decision making process, the end result is the output fuzzy variable that is defined by the set of its attributes. Each attribute is represented by one fuzzy set. Also, the defined model specifies the value of the output variable in a discrete form, i.e. in the form of a numeral. This discrete value is calculated by the defuzzification module on the basis of the output fuzzy variable. The method to be used in the defuzzification process is defined as one of the basic parameters of the model. In this paper, the defuzzification process is performed using the *lom (largest of maximum) method*. In this method, the defuzzified value is the highest x-coordinate of the maximum value of the output fuzzy set. In addition to this method, we may opt for the centroid method (defuzzified value is the x-coordinate of the central point of the output fuzzy set), the method of average maximum value, the method of the lowest maximum value, etc. The MatLab software enables visual monitoring of the operation of fuzzy modules using the so-called *rule viewer*. This tool enables viewing of the mode of operation of fuzzy modules and the look of the output fuzzy set.

The defuzzified financial scores of the business based on the application of the above model are as follows:

- For 31 December 2002, the score is 0.37
- For 31 December 2003, the score is 0.33
- For 31 December 2004, the score is 0.31
- For 31 December 2005, the score is 0.54

It can be said that the financial standing of the business is satisfactory in some measure, where such measure is expressed as the resulting defuzzified value. For instance, the financial position of the business in 2005 is satisfactory in the measure of 0.54. Here we should take into account that the resulting score may range from 0 to 1. As in the case of the model presented in the previous chapter, a final decision to accept the resulted score may be reached by comparing the resulting score with a predefined reference value, and also the decision maker may be given freedom to decide on his own whether the score is acceptable or not.

4. Classical or fuzzy approach – comparative analysis

Previous chapters presented two models of assessing financial standing of a business. These two models differ in terms of their basic modelling approach.

- In the first model, a ***classical*** approach is adopted. Discrete values, i.e. number, are assigned to the company standing indicators. The final score is the result of the weighted sum of indicator values, where each indicator is assigned a weight.
- The second model is based on a ***fuzzy approach***. Indicators are treated as linguistic variables values of which are represented by fuzzy sets. The final score is obtained on the basis of defined inference rules and presented in the form of a fuzzy set and defuzzified discrete score.

This chapter deals with basic characteristics of the given two approaches. Also, comparative analysis will be made to compare two models and a conclusion drawn on the advantages and disadvantages that one model potentially has over the other.

For the purpose of testing basic and key characteristics of models and with an aim to make a comparison, the following analyses will be conducted:

- Analysis of results for extreme values of input variables
- Analysis of the monotony of models
- Analysis of the sensitivity of models to the change of input values.

When comparing the results of two previously mentioned different concepts, we should bear in mind that the application of the classical model results in scores ranging from [0, 100], while the fuzzy model results in scores ranging between [0, 1]. Such intervals enable us to make a simple comparison of resulting scores either by dividing classical scores with 100, or by multiplying the score in the fuzzy model with 100.

4.1. Analysis of results for extreme values of input variables

Let us have a look at the values of input variables (financial indicators) in the following two extreme cases:

Case 1

Values of financial indicators are extremely bad (Table 9).

By applying classical and fuzzy models for the case of extremely bad values of input variables, the following scores are obtained:

- Classical model – financial score is 0
- Fuzzy model – financial score is 0.

Thus, both models result in expected extremely bad financial scores.

Table 9. Extremely bad values of financial indicators

Financial indicators	
Extremely bad values	
Indicator	**Values**
Quick liquidity ratio	0.10
Sources of long-term financing ratio	-0.10
Liquid assets/total assets %	0.10
Equity ratio %	0.10
Working capital turnover	0.10
Return on assets	-0.10
Debt to equity ratio	-0.10

Let us have a look now at the case of extremely good financial indicators and the resulting scores.

Case 2

Financial indicator values are extremely good (Table 10):

Table 10. Extremely good values of financial indicators

Financial indicators	
Extremely good values	
Indicator	**Values**
Quick liquidity ratio	2.00
Sources of long-term financing ratio	1.00
Liquid assets/total assets %	100.00
Equity ratio %	100.00
Working capital turnover	4.00
Return on assets	60.00
Debt to equity ratio	0.00

By applying classical and fuzzy models for the case of extremely good values of input variables, the following scores are obtained:

- Classical model – financial score is 100
- Fuzzy model – financial score is 1

Thus, both models result in expected extremely good financial scores.

On the basis of presented cases, it can be concluded that both models «react» well to extreme values of input variables. Thus, extreme values of input variables result in extreme financial scores.

4.2. Analysis of the monotony of models

Let us consider now three different cases of input financial indicator values. We can call them 'good', 'medium' and 'bad' values. Those values are characterized with the situation that all financial indicator values in a «bad» example are worse than the values in the «medium» case. Also, all values of financial indicators in a «medium» case are worse than the values in a «good» case. In symbols it can be presented as:

'bad' values < 'medium' values < 'good' values

We can check now what scores are obtained on the basis of classical and fuzzy models for these three values of financial indicators.

Case 1

'Bad' values of financial indicators are presented in the Table 11.

Table 11. 'Bad' values of financial indicators

Financial indicators	
´Bad´ values	
Indicator	**Values**
Quick liquidity ratio	0.30
Sources of long-term financing ratio	0.20
Liquid assets/total assets %	30.00
Equity ratio %	25.00
Working capital turnover	1.00
Return on assets	10.00
Debt to equity ratio	2.00

By using classical and fuzzy models for the case of 'bad' values of input variables, the following scores are obtained:

- Classical model – financial score is 32.5
- Fuzzy model – financial score is 0.2.

As expected, 'bad' values of input variables as a result have relatively low financial scores both in the classical and fuzzy model. We can now compare such scores with scores for 'medium' and 'good' values of input variables.

Case 2

'Medium' values of financial indicators are shown in the Table 12.

By using classical and fuzzy models for the case of 'medium' values of input variables the following scores are obtained:

- Classical model – financial score is 42.6
- Fuzzy model – financial score is 0.42.

The scores obtained as a result of 'medium' values of financial indicators are higher than the scores resulting from the 'bad' values of input variables in both models – classical and fuzzy model.

Table 12. 'Medium' values of financial indicators

Financial indicators	
´Medium´ values	
Indicator	**Values**
Quick liquidity ratio	0.60
Sources of long-term financing ratio	0.40
Liquid assets/total assets %	55.00
Equity ratio %	45.00
Working capital turnover	2.00
Return on assets	20.00
Debt to equity ratio	1.50

Case 3

'Good' values of financial indicators are shown in the Table 13.

By using classical and fuzzy models for the case of 'good' values of input variables, the following scores are obtained:

- Classical model – financial score is 70
- Fuzzy model – financial score is 0.66.

The scores resulting from 'good' values of financial indicators are higher than the scores resulting from the 'bad' and ‘medium’ values of input variables in both – classical and fuzzy model.

Table 13. 'Good' values of financial indicators

Financial indicators	
´Good´ values	
Indicator	**Values**
Quick liquidity ratio	0.80
Sources of long-term financing ratio	0.60
Liquid assets/total assets %	75.00
Equity ratio %	65.00
Working capital turnover	3.00
Return on assets	25.00
Debt to equity ratio	1.00

The table 14 shows total scores for the three cases.

Table 14. Scores for the three cases of financial indicator values

	'Bad' values	***'Medium' values***	***'Good' values***
Classical model	32.5	42.6	70
Fuzzy model	0.2	0.42	0.66

On the basis of three shown cases it can be seen that both models, classical and fuzzy, are characterised by monotony, i.e. if values of input variables are:

'bad' values < 'medium' values < 'good' values

then the financial scores resulting for such values have the same characteristics, which can be marked in the form of symbols as:

'bad' score < 'medium' score < 'good' score

This monotony is a key indicator showing the validity of presented models. Also, it shows that a financial score obtained by means of those models corresponds to our intuitive representation of scoring

Please note that it is to be expected that two observed models result in different scores for the same values of input variables. The classical model is based on scores of individual indicators allocated with different weights, while the fuzzy model is based on fuzzified indicators and inference rules. Naturally, it is possible to adjust both models by changing weights and inference rules, in order to adapt them to the greatest possible extent to the needs and preferences of users, i.e. financial decision makers.

4.3. Analysis of the sensitivity of the model to the change of input values

The previous two chapters showed that both models, classical and fuzzy, have characteristics supporting their validity. This chapter shows the reasons why fuzzy approach is more realistic, i.e. it points to the desired feature present in the fuzzy model and lacking in the classical model.

As already mentioned, the determination of financial standing and business success does not have a discrete but like most other real problems, a continuous character. The problem in the classical, non-fuzzy approach is seen in the fact that *small changes in the values of input variables may result in significantly different output results*. This problem is solved by applying fuzzy modelling where fuzzy sets are assigned to financial indicators. This is how it is ensured that small differences in values of input variables do not result in significant differences in output results.

This can be illustrated in the following two cases:

- Minimum change in value of one financial indicator
- Minimum change in value of all financial indicators

Case 1

It is shown below what financial scores are obtained through classical and fuzzy models in case of slight changes in the value of the return on assets.

Table 15 shows values of input variables.

By applying classical and fuzzy models to these values of input variables, the following scores are obtained:

- Classical model – financial score is 65
- Fuzzy model – financial score is 0.84

The scores resulting by applying classical and fuzzy models are relatively high on account of good values of financial indicators, i.e. financial indicators suggest a good financial position of the business in question.

If we now apply this model to the same values of input variables, with the exception of a change in a return on assets for 0.01, i.e. it is not 49.99 anymore but 50, the following financial scores are obtained:

- Classical model – financial score is 75
- Fuzzy model – financial score is the same

Table 15. Values of financial indicators

Financial indicators	
Indicator	**Values**
Quick liquidity ratio	1.00
Sources of long-term financing ratio	0.60
Liquid assets/total assets %	70.00
Equity ratio %	75.00
Working capital turnover	2.60
Return on assets	***49.99***
Debt to equity ratio	3.00

The scores resulting from the application of both models are still relatively high owing to the fact that the same (with a slight change) i.e. good values of financial indicators are observed, as in the previous example.

However, a very slight change in the value of an input variable has resulted in a great change in the financial score calculated on the basis of the classical model. The score calculated on the basis of the fuzzy model remained unchanged, which is in line with the real situation, i.e. it is realistic that such a minimal change in the value of only one financial indicator should not affect the final financial score of a business.

Case 2

In the following text we present the financial scores resulting from the application of the classical and fuzzy models in the case of a slight change in the value of all input variables.

The table 16 shows values of input variables.

When we apply classical and fuzzy models to such values of input variables, the following financial scores are obtained:

- Classical model – financial score is 40
- Fuzzy model – financial score is 0.49.

Table 16. Values of financial indicators

Financial indicators	
Indicator	**Values**
Quick liquidity ratio	0.99
Sources of long-term financing ratio	0.39
Liquid assets/total assets %	29.99
Equity ratio %	59.99
Working capital turnover	0.99
Return on assets	49.99
Debt to equity ratio	1.50

Let us observe now the values of financial indicators given in the Table 17, which are slightly different from the values presented in the previous table. By applying classical and fuzzy models to these values of input variables, the following financials scores are obtained:

- Classical model – financial score is 76.25
- Fuzzy model – financial score is 0.50.

Hence, the classical approach results in the score being significantly different from the previous one, while by applying the fuzzy approach the resulting score is only for 0.01 different from the previous one. *This case also shows that the fuzzy approach is more realistic* due to the fact that it is realistic to expect that the scores calculated on the basis of slightly different financial indicators are also slightly different.

Table 17. Values of financial indicators

Financial indicators	
Indicator	**Values**
Quick liquidity ratio	1.00
Sources of long-term financing ratio	0.40
Liquid assets/total assets %	30.00
Equity ratio %	60.00
Working capital turnover	1.00
Return on assets	50.00
Debt to equity ratio	1.49

To conclude this chapter, based on everything we presented in this paper, it can be said that, apart from having a validity, the fuzzy model is suitable for use in real situations and practical cases of assessing financial position and success of business operations.

5. Conclusion

In real circumstances decision to grant credit to a certain business is taken based on a number of criteria, the values of which are adequately compared. This paper proposes a financial decision support system.

The first model is based on the classical decision support systems. This model combines criteria values in a suitable way in order to come to a final score of a business. Since it takes into account several relevant criteria for scoring the business standing, this model is suitable for use in practical situations. However, its main disadvantage is seen in the fact that in some cases very small changes of the value of input parameters or the value of given indicator result in a significantly different score for a given company, and thus resulting in a different final credit decision.

This problem is successfully overcome by introduction of fuzzy concepts into the decision making process. Fuzzy logic represents a powerful tool for modelling situations that are characterised by the presence of uncertainty, inaccuracy and incomplete information. Due to such characteristic, fuzzy sets have been used as a means to model the values of given parameters that are used as the basis for evaluation of the given business. In this way, the values of indicators are no longer expressed in numbers but in fuzzy sets. Thus modelled indicators are combined to determine the total score of the analysed business using the fuzzy inference rules. Hence, the presented model represents an example of a fuzzy expert system with all its significant characteristics and elements: knowledge base, inference mechanism, and fuzzification and defuzzification modules.

The main part of this paper lies in comparing these two models and presenting the facts that back up the superiority of fuzzy expert system as compared to the classical financial decision support system.

6. References

1. Čupić, M., Cvetković, S.: Intelligent decision support system (DSS) for financial management based on fuzzy sets, Belgrade, 1999.
2. Čupić M, Tummala R., Suknović M.: Odlučivanje: formalan pristup /Decision Making: A formal approach/, Faculty of Organizational Sciences, Belgrade, 2003.
3. Holsapple, C.W., Whinston, A.B.: Decision support systems. A knowledge-based approach, West Publishing Co., 1996.
4. Žarkić Joksimović, N.: Upravljanje finansijama. Osnove i principi /Financial Management. Basic Elements and Principles/, Faculty of Organizational Sciences, Belgrade, 2005.
5. Klir, G. J., Yuan, B.: Fuzzy sets and fuzzy logic, theory ond applications, Prentice Hall, London, 1995.
6. Radojević, G.: Prilog razvoju metodologije podrške finansijskom odlučivanju, /Towards Development of Methodology to Support Financial Decision Making/, PhD thesis, Faculty of Organizational Sciences, Belgrade.
7. Mockler, R.J.: Knowledge-based systems for management decision, Prentice-Hall, Inc., 1989.
8. Vitt, E., Luckevich, M., Misner, S.: Business Intelligence. Making Better Decisions Faster, Microsoft Press, 2002.
9. Turban E., Aronson J.E.: Decision support systems and Intelligent systems, Prentice Hall 2001.

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