Fuzzy model investic do High-tech projektů

Fuzzy Model of Investments into High-tech Projects

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Abstract:
Purpose of the article: Relations among parameters of High-tech projects are very complex, vague, partially inconsistent and multidimensional. Optimal decisions to invest into High-tech companies require top field experts and knowledgeable investors. Therefore the conventional methods of investments analysis are not relevant. Therefore fuzzy logic is introduced.
Methodology/methods: A fuzzy knowledge base is a flexible framework for acquisition of vague inconsistent knowledge items which are typical for knowledge economics and consequently for High-tech projects. The pooling of the records and / or observations represents a trade-off between minimal modification of the original data and elimination of inconsistencies among available sets of data.
Scientific aim: The paper presents a detailed description of fuzzy model of investment decision making into High-tech firm's projects. A set of conditional statements was used to formalize the effects of selected variables on investment feasibility of High-tech projects. The main aim is to quantify feasibilities of High-tech projects risk investors make good /not bad decisions.
Findings: A set of 50 observations of High-tech companies was transformed into a set of 50 conditional statements using 14 variables. The result is the fuzzy model, which can be used to answer investors' queries. Two queries are answered and presented in details as an example and as a nucleus of a fuzzy dialogue investor – computer.
Conclusions: The main problem is the sparseness of the fuzzy model. Many fuzzy similarities are relatively low and the decision process is therefore often problematic. A much more complex set of variables must be applied to specify the fuzzy model to increase reliability of predictions and decisions.

Keywords: Fuzzy Interpolation, Fuzzy Knowledge Base, Fuzzy Model, Fuzzy Reasoning, Investment Decision Making, High-tech Projects

JEL Classification: C51, M21

Introduction

In the current era of extremely fast changing economy, the High-tech industry is an important driving force to promote the development of the country's economy. However, investing in this field needs a lot of capital and the investment is complicated by uncertain results and is therefore very risky.

New High-tech projects require often relatively large investment. A High-tech related investment is an ad hoc and time consuming process that requires qualified field experts and knowledgeable investors. The investment is always doing by more than one investor.

Most of the techniques employed for the analysis of complex High-tech problems possess analytical or statistical natures. Unfortunately these precise mathematical tools do not always contribute as much as is expected towards a full understanding of complex task. We cannot expect to be able to analyse completely rigorously a complex real problem using conventional techniques (analytical or statistical).

A simple and efficient way to minimise the loss of valuable knowledge represented by a set of heterogeneous clusters of observations is fuzzy reasoning. A fuzzy set represents an optimal trade-off between the absolutely precise number and a vague verbal quantification (Li *et al.,* 2009, Hurme *et al.*, 1993).

Fuzzy set theory is based on the premise that the key elements in human thinking are not numbers but words. The most important feature of human thinking is the not yet well-understood ability to extract from a collection of masses of data only such items of knowledge which is relevant to the task at hand (Zimmermann, 2001, Filev *et al.,* 1991).

1. Fuzzy reasoning

There are several different fuzzy reasonings. High-tech investors are not willing to invest too much time to study complex formal theories. They are not mathematicians or artificial intelligence experts. Therefore a simple fuzzy reasoning is chosen to solve the below given tasks.

A linguistic value which is a "value" that is given by words, *e.g.* high, small, low, see *e.g.* (Martino *et al.*, 2011, Chen *et al.*, 2012).

Let us take as an example of a verbal variable the business fit (BUF). To quantify expert knowledge, a set of verbal values, *i.e.* a dictionary, is needed. Such the BUF "verbal dictionary" could be the following set:

Very low, low, medium, high, and very high.

The linguistic value is transformed into the fuzzy set by the specification of a grade of membership. For example, the verbal value low BUF is transformed into a fuzzy set by the grade of membership function given in Figure 1. A typical low (L) BUS is (Chen, 2010, Pei, 2012):

$$b < BUS < c \,, \qquad (1)$$

where (see Figure 1)

$$\mu_M(BUS) = 1 \,, \qquad (2)$$

is the grade of membership of the numerical value BUS in fuzzy set *M.* The values of BUS with the grade of membership equal to 1. Therefore they are typical low BUSs.

There are two fuzzy intervals namely:

$$\begin{aligned} & a < BUS < b \text{ or } c < BUS < d \\ & \textit{if } a < b \text{ or } c < BUS < d \\ & \text{then } 0 < \mu_M(BUS) < 1 \,. \end{aligned} \qquad (3)$$

These intervals represent BUS numerical values which belong partially to the fuzzy set low BUS (Chen, 2010, Pei, 2012).

2. Fuzzy interpolation

A simple fuzzy reasoning can be explained using a strong analogy between reasoning and multidimensional interpolation. Let us suppose that

$$Y = \varphi(X_1, X_2, ..., X_n) \,. \qquad (4)$$

The only available information about the complex function (4) is a matrix

$$M\left[m \cdot (n+1)\right], \qquad (5)$$

where *m* is the total number of different investments. The last column gives the values of the dependent variable *Y*.

The relation (4) is approximated by a function

$$Y = \Phi\left(X_1, X_2, ..., X_n\right), \qquad (6)$$

which is used to "substitute" the unknown function (4).

To use the investment results (6) directly, an interpolation or correlating algorithm is needed. To cover obvious requirements which can be easily deduced from the typical features of the results of measure-

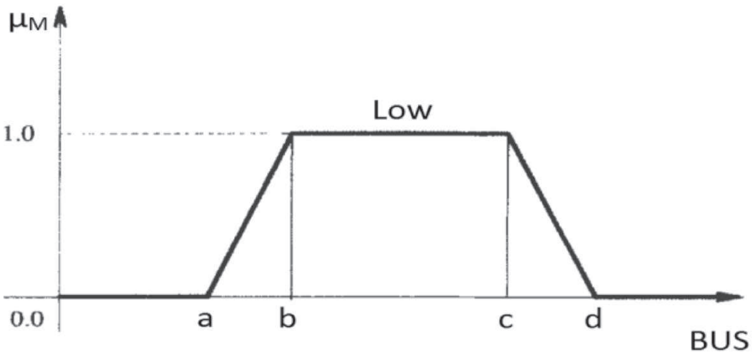

Figure 1. Piecewise linear descriptions of the grade of membership function. Source: Baah et al., 1997.

ments / observations, a suitable interpolation algorithm must be capable of interpolating data which are multidimensional, non-equidistantly spaced, variously accurate (vague), spares. Data have different weights for variables and measurements / observations assigned by different users.

The theory of interpolation does not offer an algorithm which is robust enough to cover all practical situations. The fuzzy reasoning algorithm is therefore used to "interpolate" or "correlate". The interpolation itself is done by a fuzzy reasoning mechanism of which there are many; see *e.g.* (Kilic *et al.*, 2004, Carrasco *et al.*, 2012).

The complex mathematical details of fuzzy reasoning are not too relevant for the end user / non mathematicians. Let us rely on a simple geometrical interpretation of two-dimensional interpolation algorithm [$n = 1$, see eq. (4)].

Figure 2 shows a typical situation in which there are two clear clusters of measurements and several measurements scattered outside these groups. These clusters represent two sets of measurements performed by two experimenters. A conventional algorithm (using the standard best fit philosophy) gives the approximation curve, see Figure 2.

However, because of the very nature of the best fit algorithm, all experimental outcomes are taken into account in "positioning" the curve. Any query, however, is "local". Is it a good idea to let the answer be affected by all experimental results? Would it be better if the closest measurements to the query were considered as more relevant?

A graphic representation of a one-dimensional interpolation [$n = 1$, see eq. (4)] is presented in Figure 3. There are m numerical values V of the independent variable X and the corresponding numerical values W of the dependent variable Y (6):

$$X \equiv \{V_1, V_2, ..., V_m\},$$
$$Y \equiv \{W_1, W_2, ..., W_m\}. \quad (7)$$

The one-dimension query Q is represented by its numerical value q. There is no numerical value of the independent variable X in expression (7) that is equal to the value q.

Imagine now that a source of light L is pleased at a distance H below the numerical value q in Figure 3. The light beam is totally focused and is represen-

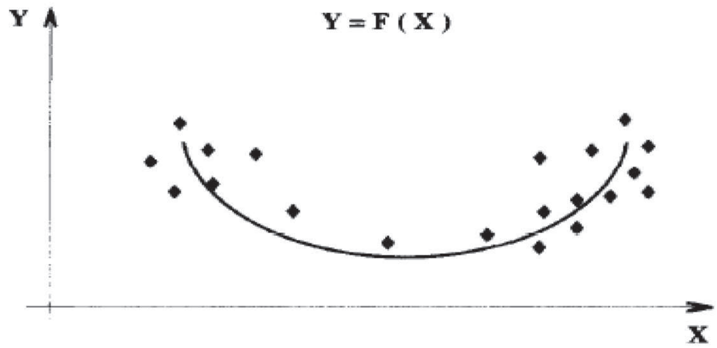

Figure 2. A typical approximation of a two dimensional data set. Source: Baah et al., 1997.

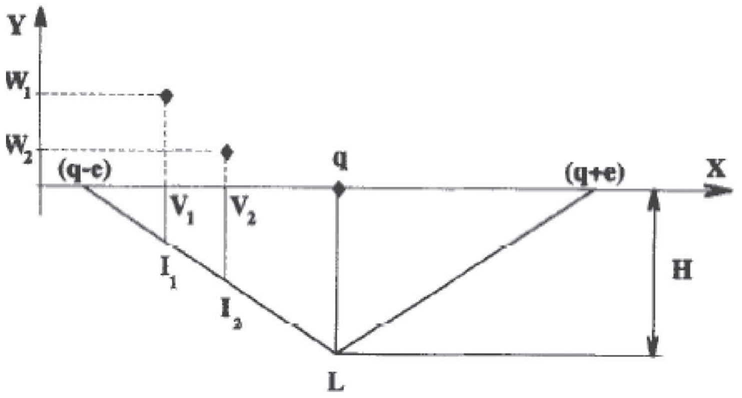

Figure 3. An optical analogy of fuzzy defocusing. Source: Baah et al., 1997.

ted by an infinitely narrow interval Lq. The whole X-axis is dark, the only exception being the point q. A one-dimensional defocusing algorithm smoothly transfers the light interval Lq into a light triangle

$$(q-e), L, (q+e)\,. \tag{8}$$

Let us suppose that the triangle covers only the following two values on the X-axis which are of interest (corresponding to the X-coordinates of points W_1 and W_2)

$$V_1V_2 \tag{9}$$

and that the light intensity at these points is represented by the length of the lines

$$V_1I_1, V_2I_2\,. \tag{10}$$

The light intensity is "proportional" to fuzzy similarity s of the query q and two numerical values V_1, V_2. The following weighted average is thus used to "interpolate" the value of the dependent variable which corresponds to query q

$$\left(W_1 \cdot V_1I_1 + W_2 \cdot V_2I_2\right) / \left(V_1I_1 + V_2I_2\right). \tag{11}$$

A general formula for one-dimensional interpolation is a fairly straightforward extenuation of the expression in Eq. (11). The key problem is the choice of the height H and the defocusing algorithm that is the algorithm that controls the defocusing e.

There are several geometrical interpretations of fuzzy reasoning as an interpolation algorithm, see *e.g.* (Bloch, 2008, Chen *et al.*, 2011). The one presented above reflects all substantial features of the fuzzy reasoning as an interpolation algorithm. The one presented above reflects all substantial features of the fuzzy reasoning algorithms used below. However, equally efficient interpolation can be based on the simple idea of moving the light source L (see Figure 3) away from the point q without any additional defocusing.

3. Fuzzy model

A fuzzy model is a set of conditional statements (Turunen *et al.*, 1984):

If $A_{1,1}$ and ... and $A_{1,n}$ then B_1 or
If $A_{2,1}$ and ... and $A_{2,n}$ then B_2 or
....
If $A_{m,1}$ and ... and $A_{m,n}$ then B_μ (12)

where fuzzy sets

$$A_{i,j}, B_i;\ i = 1, 2, ..., m,\ \ j = 1, 2, ..., \tag{13}$$

are one dimensional fuzzy sets and can be easily specified or modified using points *a, b, c, d* (Figure 1) for each set.

There are many different fuzzy reasoning algorithms. However, our industrial experience showed that the most important feature of a reasoning algorithm is its transparency and simplicity (Dubois *et al.*, 1991, Lee *et. al*, 1990). In practice any engineer wants to know why and how a certain conclusion is reached (Dohnal, 1983).

A transparent fuzzy reasoning / answering formalism:

$$Q \rightarrow \text{fuzzy model (12)} \rightarrow R \tag{14}$$

is based on fuzzy similarity. A one-dimensional fuz-

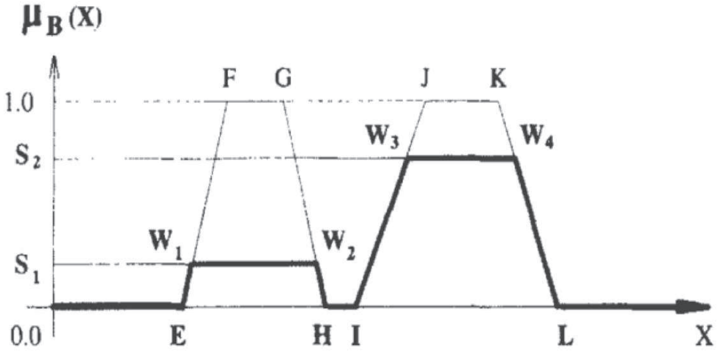

Figure 4. The fuzzy answer as a union of „weighted" fuzzy sets B1 and B2. Source: Baah et al., 1997.

zy set R is an answer to a given (chosen) n-dimensional fuzzy query Q:

$$Q = Q_1 \text{ and } Q_2 \text{ and ... and } Q_n , \quad (15)$$

where Q_i is a one-dimensional fuzzy. Set the similarity s of two n-dimensional fuzzy sets V, W is

$$s(n,V,W) = \min \top (l \leq j < n) \left\{ \max \top Xj \left\{ \left\{ \min \left\{ \left[\mu_{\downarrow} Vj (X_{\downarrow} j) \right] \right\} \right\} \mu_{\downarrow} Vj (X_{\downarrow} j) \right\} \right\} .(16)$$

The i-th statement (12) is activated by the n-dimensional fuzzy query Q (15) if the fuzzy set r_i,

$$r_i = A_{i,1} \text{ and } A_{i,2} \text{ ... and } A_{i,n} \quad (17)$$

and Q are fuzzy similar (16):

$$s(n,Q,r_i) , \quad (18)$$

Set $w(Q)$ of those statements which are activated by the query Q is:

$$w(Q) = \{i \mid s(n, r_1, Q) > 0\} . \quad (19)$$

Answer R of fuzzy model (12) to query (15) is the following fuzzy union of B sets (12)

$$R = \bigcup_{i \in w(Q)} B_i i \in w(Q) . \quad (20)$$

Let us suppose that only two statements out of m statements (12) are activated by query Q. To be specific, let the first and the second statements be activated. Therefore, see (19),

$$w(Q) = \{1,2\} . \quad (21)$$

Let $B_1(T)$ be $EFGH$ (Figure 4) and $B_2(T)$ be $IJKL$. The fuzzy "answer" R (20) of the model (12) is represented by the fuzzy set $EW_1W_2HIW_3W_4L$ (Figure 4).

Quite often a fuzzy model is only a part of a more complex and perhaps conventional calculation is based on numbers. Therefore a fuzzy → deterministic interface is needed to generate a numerical represent the level of knowledge inconsistency. If the interval HI is too big then the fuzzy answer gives a clear signal that the statements Nos. 1 and 2 (see (19)) are unacceptably inconsistent. This inconsistency level is amplified if the absolute values of similarities s_1 and s_2 are high and their difference is not too significant.

4. Case study: High-tech investments

A fuzzy model was used to study an ill-known relation of High-tech investments feasibility as a function of 13 variables, see Table 1. The variables were chosen by an extensive literature search, direct observations of High-tech firms and taking advantage of several field experts willing to cooperate.

The literature shows that the most important factor is an optimal integration of staff / owners. Human Resources are very important for the High-tech firm's performance. Human resource policies, practices, and activities are the bedrock of a firm's capacity for resilience (Lengnick-Hall *et al.*, 2011, Patzelt, 2010). This conclusion can be, indirectly interpreted for High-tech companies as abilities to produce meaningful results based on experience and technology knowledge (Wang *et al.*, 2012).

Table 1. Abbreviation.

Variable	Abbreviation	Dimension
Personal Impression	PAS	(%)
Experience	TRU	(%)
Level of Technology / Technology Knowledge	TEK	(%)
Innovation	INQ	(%)
Protect Ability	PRO	(%)
Growth Potential of the Company	GRP	(%)
Cash Flow	CSF	(%)
Rentability on Investment	ROI	(%)
Profitability	PFR	(%)
Debt	DBT	(%)
Inflation Expectation	IEX	(%)
Taxes	TXA	(%)
Investor' s Role	IRL	(%)
Investment Feasibility	BSF	(%)

Source: Own compilation.

Table 2. Dictionaries of all variables.

Abbreviations		See Figure 1	a	b = c	d
PAS	PA1	Low personal impression	0.01	0.15	0.25
	PA2	Medium personal impression	0.2	0.45	0.5
	PA3	High personal impression	0.45	0.75	1.00
	PA0	Not defined	0,00	0.5	1.00
TRU	TR1	Low trustworthiness/experience	0.01	0.15	0.25
	TR2	Medium trustworthiness/experience	0.2	0.45	0.5
	TR3	High trustworthiness/experience	0.45	0.75	1.00
	TR0	Not defined	0,00	0.5	1.00
TEK	TE1	Low level of technology / technology knowledge	0.01	0.15	0.25
	TE2	Medium level of technology / technology knowledge	0.2	0.45	0.5
	TE3	High level of technology / technology knowledge	0.45	0.75	1.00
	TE0	Not defined	0,00	0.5	1.00
INQ	IN1	"Slight innovation power"	0.01	0.15	0.25
	IN2	"Qualitative innovation power"	0.15	0.5	0.7
	IN3	"Technological revolution"	0.75	0.87	1.00
	IN0	Not defined	0,00	0.5	1.00
PRO	PR1	Low protect ability of the product	0.01	0.15	0.25
	PR2	Medium protect ability the product	0.2	0.45	0.5
	PR3	High protect ability of the product	0.45	0.75	1.00
	PR0	No defined	0,00	0.5	1.00
GRP	GR1	Low growth potential of the company	0.01	0.15	0.25
	GR2	Medium growth potential of the company	0.2	0.45	0.5
	GR3	High growth potential of the company	0.45	0.75	1.00
	GR0	Not defined	0,00	0.5	1.00
CSF	CS1	Low Cash Flow	0.01	0.05	0.1
	CS2	Medium Cash Flow	0.08	0.12	0.2
	CS3	Positive Cash Flow	0.15	0.75	1.00
	CS0	Not defined	0,00	0.5	1.00

Abbreviations		See Figure 1	a	b = c	d
ROI	RO1	Low ROI	0.01	0.05	0.08
	RO2	Medium ROI	0.05	0.25	0.3
	RO3	High ROI	0.25	0.75	1.00
	RO0	Not defined	0,00	0.5	1.00
PFR	PF1	Slight or no profit	0,00	0.05	0.08
	PF2	Low profitability	0.05	0.25	0.5
	PF3	High profitability	0.45	0.75	1.00
	PF0	Not defined	0,00	0.5	1.00
DBT	DP1	Low debt ratio	0,00	0.15	0.3
	DP2	Medium debt ratio	0.25	0.5	0.75
	DP3	High debt ratio	0.6	0.8	1.00
	DP0	Not defined	0,00	0.5	1.00
IEX	IE1	Low inflation rise	0.01	0.05	0.08
	IE2	High inflation rise	0.07	0.75	1.00
	IE0	Not defined	0,00	0.5	1.00
TXA	TX1	Lower capital gains tax	0,00	0.25	0.45
	TX2	Higher capital gains tax	0.3	0.75	1.00
	TX0	Not defined	0,00	0.5	1.00
IRL	IR1	Management know-how provider	0,00	0.05	0.11
	IR2	Finance provider	0.1	0.25	0.5
	IR3	Finance provider and management know-how provider	0.45	0.75	1.00
	IR0	Not defined	0,00	0.5	1.00
BSF	BS1	Low investment feasibility	0.01	0.25	0.5
	BS2	High investment feasibility	0.45	0.75	1.00
	BS0	Not defined	0.00	0.5	1.00

Source: Own compilation.

Table 3. Set of statements (see Table 1 and Table 2).

No.	PAS	TRU	TEK	INQ	PRO	GRP	CSF	ROI	PFR	DBT	IEX	TXA	IRL	BSF
1	PA2	TR1	TE2	IN3	PR1	GR1	CS2	RO1	PF2	DP2	IE1	TX1	IR2	BS1
2	PA1	TR3	TE2	IN1	PR2	GR3	CS3	RO2	PF2	DP2	IE1	TX1	IR3	BS2
3	PA2	TR2	TE1	IN3	PR2	GR2	CS2	RO1	PF2	DP3	IE1	TX1	IR2	BS1
4	PA2	TR2	TE1	IN2	PR1	GR1	CS3	RO2	PF2	DP2	IE1	TX1	IR2	BS1
5	PA1	TR1	TE2	IN3	PR1	GR2	CS2	RO2	PF2	DP1	IE2	TX1	IR2	BS1
…	…	…	….	…	….	….	….	…	…	….	…	…	…	…

Source: Own compilation.

Table 4. The query No. 1 (see Figure 1).

The other well know financial investment criteria are generated cash flow, return on investment, profitability, debt level of the firm and growth potential of the High-tech firm and less important criteria such as inflation expectation, tax system and investor role., see *e.g.* (Dixon, 1991, Mason *et al.*, 1996, Landström, 1998, Feeney *et al.*, 1999, Stedler *et al.*, 2003, Park, 2005, Sudek, 2007, Konečný, 2010, Festel, 2011).

A set of 50 High-tech investments is available; majority is related to ecology and is closely connected to research activities of Brno University of Technology.

These information items must be transferred into a fuzzy model (12), *i.e.* a set of conditional statements where $n = 13$ and $m = 50$. An important part of each fuzzy model is a set of fuzzy sets A and B, see (12), see Table 2

Abbreviation	a	b = c	d
PAS	0.01	0.15	0.25
TRU	0	0.5	1
TEK	0.01	0.15	0.25
INQ	0.75	0.87	1
PRO	0	0.5	1
GRP	0.01	0.15	0.25
PIF	0.08	0.12	0.2
ROI	0.01	0.05	0.08
PFR	0.05	0.12	0.2
DBP	0.01	0.15	0.3
IEX	0	0.5	1
TXA	0.3	0.75	1
IRL	0.2	0.35	0.5

Source: Own compilation.

Table 5. The query No. 2.

Abbreviation	a	b = c	d
PAS	0.01	0.15	0.25
TRU	0.01	0.15	0.25
TEK	0.01	0.15	0.25
INQ	0.15	0.5	0.7
PRO	0.01	0.15	0.25
GRP	0	0.5	1
PIF	0.01	0.05	0.1
ROI	0.01	0.05	0.08
PFR	0	0.5	1
DBP	0.6	0.8	1
IEX	0.01	0.05	0.08
TXA	0.3	0.75	1
IRL	0.2	0.35	0.5

Source: Own compilation.

Table 6. Answers of queries (see Table 4 and Table 5).

Query no.	Activated statement no. similarity(See Table 3)	Investment feasibility (Table 1)			Similarity[See (16)]	Answer: centre of gravity (%)
	5	0.01	0.25	0.5	0.08	
	7	0.01	0.25	0.5	0.05	
	32	0.45	0.75	1.00	0.09	
1.	10	0.00	0.5	1.00	0.08	17.50
	20	0.00	0.5	1.00	0.04	
	29	0.00	0.5	1.00	0.07	
	40	0.00	0.5	1.00	0.35	
	4	0.01	0.25	0.5	0.09	
	13	0.01	0.25	0.5	0.25	
	18	0.01	0.25	0.5	0.12	
	21	0.01	0.25	0.5	0.15	
2.	36	0.01	0.25	0.5	0.13	22.50
	11	0.45	0.75	1.00	0.01	
	19	0.45	0.75	1.00	0.11	
	15	0.00	0.5	1.00	0.12	
	27	0.00	0.5	1.00	0.11	

Source: Own compilation.

The fuzzy model characterises the following vaguely known relations, see Table 1:

$$BSF = f(PAS, TRU, TEK, INQ, PRO, GRP, PIF, ROI, PFR, DBT, IEX, TXA, IRL) \quad (22)$$

The set of statements is characterised by the first 5 statements given in the Table 3 as an example.

The queries No. 1 and No. 2 are defined as follow (see Table 4 and Table 5):

Table 6 gives the detailed specification of the fuzzy answers and their numerical representations. The numerical representation is a number which can replace the corresponding fuzzy set, for details see Table 2 and Table 6.

The fuzzy answers mentioned above are derived directly from the observations of High-tech investments; the derivation uses the fuzzy interpolation algorithm. Such an answer is more realistic and it is based on the primary information.

This technique is able to minimize loses of primary information and uncertainties in application of technical information. The Table 6 shows number of query, activated statement, the fuzzy set of BSF and similarity of each activated statement. The answer of the query is a centre of gravity of BSF's fuzzy set. The main value is the similarity of query with each statement. If the similarity is low, the model is not able to give a reasonable answer.

5. Discussion

In this case study is the similarity *s* (16) of statements and queries around 0.01–0.35. The Table 6 shows that each of the queries is similar to different statements. The answers belong to the same fuzzy set (see Table 2, and Table 6). Investments with these parameters are not acceptable.

The main problem in fuzzy reasoning is the sparseness of the fuzzy model, which is mainly caused by the model dimensionality. In reality usually no conditional statement is similar to the query under study, especially when we are speaking about a new High-tech investment.

Therefore, all similarities *s* (16) are very low and the reasoning process is problematic. A much more complex set of variables must be applied to specify the fuzzy model. However, its development is problematic due prohibitively information intensity, for more information see *e.g.* (Dohnal *et al.*, 2008). It must be stressed that there are many unsolved vague reasoning problems. This fact gives conclusion that vague modelling is always rather subjective.

Despite the shortcomings, this model can be used widely in the area of the risky High-tech project investment to support investors in decision making. In addition, the method can be applied to another multi-attribute decision-making problem which attribute values is not easy to quantify, such as the human resources evaluation, science and technology fund project evaluations, production technology program evaluation etc.

Conclusion

As outlined previously, the fuzzy reasoning is based on a fuzzy interpolation algorithm. This algorithm can minimize loss of information and depress spreading of uncertainties in application of vague information. The practical application proves if the method is feasible. A fuzzy model, a set of conditional statements, was used to formalize the mention above 13 variables on investment feasibility.

A set of 50 observations of High-tech companies is available as the nucleus of the fuzzy model. The data set was transformed into a set of 50 conditional statements using 14 variables. The resulting fuzzy model can be used to answer a broad spectrum of queries. To demonstrate the procedure and interpretation of results two queries are answered.

Investments into High-tech companies are important problems which can be characterised as high risks and high profit tasks. The paper introduces a concept of fuzzy interpolation into an analysis of High-tech investments.

The paper studies special version of interpretation of fuzzy reasoning problems. The main practical difficulty is the sparseness of the fuzzy model, which is caused by the high model dimensionality. In reality usually no conditional statement is similar to the query under study.

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