Evaluation of the Quality of the Entrepreneurial Environment on the Basis of Fuzzy Logic

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Abstract

Investor's risk involves both economic and non-economic factors, which are evaluated by ratings agencies. Within this context, estimates are calculated of the percentage value of the quality of the entrepreneurial environment "*p*" for selected countries in Europe and Asia. They are based on the modified values of the indices of the partial components of the quality of the entrepreneurial environment (levels of corruption, economic and political stability). The partial components of the rating evaluation are processed by means of fuzzy logic, which enables the description of vague and uncertain input data and sociological-psychological factors that occur during managerial tasks. Fuzzy logic is based on the fundamentals of classic propositional logic, whereby the truth-value of each A statement is generalized as $|A| \in \langle 0,1 \rangle$ and is interpreted as the extent or degree of its truthfulness. Compared to the statistical approach, fuzzy logic is discussed and evaluated in terms of particular managerial tasks.

Keywords: fuzzy logic, entrepreneurial risk, ratings agency, sociological-psychological factors

Introduction

In complex situations that are characterized by unspecified influences and which result in uncertainty, people usually follow the normative rules for a particular situation, or act on the basis of their knowledge and experience, or both. Decision-making and management based on rules is quite easy and reliable, especially in cases of situational management, whereby each situation can be reliably identified and treated in accordance to one relevant rule (Polikar 2006).

In situations where the choice of the relevant rule is not unambiguous it is necessary to accept a compromise. This reflects the fact that the concepts and procedures on which rules are usually based are often vague and ambiguous; who knows the exact meaning of appropriately, carefully, or thoroughly? However, this vagueness and ambiguity are not detrimental in practice because they enable, for example, an experienced financial consultant to "customize" a client´s financial plan on the basis, for example, of their tendency to take risks and their preference for profit.

In light of the large number of concurring factors with sociological-psychological characteristics, many experts in various management branches find themselves in a similar situation to the experienced financial consultant. Managerial decisions are decisions that concern future outputs, which are always uncertain in some aspects (Froot and Stein 1998). This uncertainty is associated with a number of risks, for which a number of quantitative and qualitative procedures are used in order to minimize them. For example, the evaluation of the investment risks of a project are, as standard, quantified on the basis of the expected net value of cash flows after taking into consideration two risk components: a) the possibility of the occurrence of various results as a consequence of the existence of various scenarios - this risk component reflects the existence of external influences, which cannot be excluded (e.g. variations in price levels, demand levels, macro-economic influences, etc.); b) the fact that the particular income from the given project usually fluctuates around its expected value over time - this component reflects internal influences, which the investor may have under their control to a certain extent (Myers 2015; McNeil et al. 2015; Wiesemann et al. 2010). Hašková (2016) also discusses how the standard investment risk can be extended by additional non-economic components in the form of political or environmental risks (e.g. war, expropriation, sanctions, natural catastrophes, etc.).

This article aims to extend the standard procedures for the quantification of an investor's risk by means of fuzzy logic, which primarily concerns the processing of vague values which are the products of uncertain ideas, untested concepts and general thinking. The use of fuzzy logic is used in various managerial disciplines to search for the answers to problems burdened by uncertainty (see Kahraman et al. 2016; Gitinavard et al. 2015; Dong and Li 2016; Chiu and Park 1994).

In this article, fuzzy logic is applied to resolving a practical managerial task, whereby an investment consultant must quantitatively evaluate the quality of the prevailing entrepreneurial environment, whilst taking into consideration the relationship of a particular investor to risk. This evaluation is based on the values of indices (on a scale of 0 to 100) for selected countries in Europe and Asia as published by specialised world ratings agencies (see Table 1). As part of the solution fuzzy logic shows how the ambiguousness, vagueness and uncertainty of the managerial problem can be solved with suitably formulated rules and procedures.

Materials and Methods: fundamentals of fuzzy logic

In the world of expert management, vaguely defined concepts and systems are usually represented by linguistic variables and their linguistic values (so-called terms); the word "linguistic" is used within the context of "communicated in the natural language". The desired relationship between the input and output linguistic variables is determined by complex rules. The tool with which to mathematically solve this type of task is fuzzy logic (for further details on fuzzy logic see, for example, Ross (2010)).

Fuzzy logic may be seen as a certain generalization of classic (two-value) propositional logic (for further details on aspects of propositional logic see, for example, Peregrin (2016) or Peregrin and Svoboda (2016)). Under fuzzy logic, the probability values P (truth) and N (untruth) for propositions A and B are replaced by the numbers 1 and 0 respectively. The truth-values for proposition A and B are therefore designated as $|A| \in \{0,1\}$, or $|B| \in \{0,1\}$ respectively. The truth charts for conjunction, disjunction and negation are expressed in terms of the numerical characteristics of these operators: $|A \wedge B| = \min\{|A|,|B|\}$, $|A \vee B| = \max\{|A|,|B|\}$, $|\neg A| = 1 - |A|$. This, for example, implies that $A \rightarrow B$ (irrespective of whether it does or does not reflect the causality of the phenomena) is $|A \rightarrow B| = |\neg A \vee B| = |\neg(A \wedge \neg B)| = \max\{1 - |A|,|B|\} = 1 - \min\{|A|,1 - |B|\}$.

In practice, the rule in the form of pair (A,B) is also considered to imply (although this is not strictly in adherence with the concept of formal logic) that the "answer to A is B". The common feature of implication is that it is also an asymmetrical relationship. However, its similarity with the "if ... then" implication is more formal than factual because $|A|$ and $|B|$ in the (A,B) rule are not fully independent of each other i.e. the degree to which the choice of the (A,B) rule, as well as answer B, is justifiable, should not exceed the degree of certainty that situation A really occurred. Unlike implication, the rule does not claim to be universally truthful. It is for this reason that it may be interpreted as a generalization, which allows for exceptions. Nevertheless, when $|A| = 0$, the justifiability of the choice of the rule $|(A,B)| = 0$, regardless of $|B|$. In contrast, when $|B| = 0$, it is clear that, regardless of $|A|$, the (A,B) rule was not chosen. The logical structure of the rule is therefore factually closer to the conjunction of its both sides (left side A and right side B) than to implication, so that $|(A,B)| = |A \wedge B| = \min\{|A|,|B|\}$. It is in this manner that the rule is viewed in this study.

To transform classic propositional logic into fuzzy logic it is sufficient to exchange the two-element set $\{0,1\}$ of truth values of propositions for interval $\langle 0,1 \rangle$ and to interpret the number $|A| \in \langle 0,1 \rangle$ as the extent or degree to which proposition A is true. Within the scope of fuzzy logic it is possible to define the fuzzy set as the U set of all the considered objects (universe of discourse) under the rule $A = \{(x, \mu_A(x)): x \in U\}$, whereby $\mu_A(x): U \rightarrow \langle 0,1 \rangle$ is the function of the affiliation of elements of the universe to fuzzy set A in the form $\mu_A(x_0) = |x_0 \in A|$. It is clear, that should $\mu_A(x): U \rightarrow \{0,1\}$, the fuzzy set transforms into a standard set. Fuzzy sets are suitable tools for the formalization of linguistic variables for vaguely defined tasks, which enable the involvement of the knowledge and

experience of experts in generating a solution in terms of suitable choices for decision-making rules.

Methodology for the application of fuzzy logic to generate solutions for tasks with vague inputs and procedures

The general procedure for generating a solution to a problem on the basis of fuzzy logic is schematically shown in Figure 2. Prior to formulating the fuzzy model, the task assignment must be translated from natural language into the language of fuzzy logic. This involves arranging the input linguistic variables "n" into a n-tuple under which the specific sequence of variables will be maintained. Each member of this n-tuple (e.g. input linguistic variable A) is subsequently assigned its set {Ai: i = 1,2,…,m} of formalized terms (fuzzy sets defined by functions of affiliation $0 \leq \mu_{Ai}(x) \leq 1$ over the domain of U_A of basis values for variable A (i.e. $x \in U_A$) – see Figure 1). The form and position of the non-zero fragments of curve μ_{Ai} is attributed by the expert to the distribution of basis values of domain U_A. The set {Bj: j = 1,2,…,k} of formalized terms is subsequently analogically assigned to one output linguistic variable B.

It is clear, that in total, "m" possibilities exist for various selections of the Ai term from the set {Ai: i = 1,2,…,m}. If all the term sets of input variables are of the same quantity, then we receive in total, by this method of term selection (each input variable is only selected from its set), m^n n-tuples of selected terms. If T is used to identify the set of n-tuples of terms selected, which is graphically represented by φ: T → {Bj: j = 1,2,…,k}, whereby $\alpha_n \in$ T, $\beta \in$ {Bj: j = 1,2,…,k} and $\varphi(\alpha_n) = \beta$, then the pair ($\alpha_n$, β) forms an inference rule. During the formulation phase of the inference rules, the expert has the opportunity to bring in their knowledge and experience into the model by selecting the choice of terms to the right sides of the inference rules (the number of various sets of rules which can be produced is equal to the number "k" raised to the power "m^n"). The expert does not have this opportunity any more during the task solution phase.

The procedure for generating a fuzzy model solution consists of five steps (see Figure 2 – inside the large frame). The value $x_0 \in U_A$, being a member of the current input n-tuple of basis values of linguistic variables, is assigned the terms Ai, where $\mu_{Ai}(x_0) > 0$ (see Figure 3), during the process of "fuzzification". If x_0 lies in the interval above which the positive parts of curves μ_{Ai} and μ_{Ai+1} of the two terms overlap, then the term Ai is selected by it with the truth value $\mu_{Ai}(x_0)$, term $Ai+1$ with the truth value $\mu_{Ai+1}(x) = 1 - \mu_{Ai}(x)$, whereas if the opposite is the case, one term is selected by it (e.g. Ai) with the truth value $\mu_{Ai}(x_0) = 1$ (from Figure 3 it follows that at least one term has to be selected with the value x_0). The value $\mu_{Ai}(x_0)$, respectively $\mu_{Ai+1}(x_0)$ or only $\mu_{Ai}(x_0) = 1$, can be considered for the rate of justifiability for the selection of the respective term. The situation is identical for the other members of the current input n-tuple of basis values. If $\mu = 1$ can be applied to all of them, then only one n-tuple of α_n^* terms is selected by this input, which in view of the fact that no two members of it are part of the same set of terms, means that it is a symbolic notation (selected terms and their split in the n-tuple)

that is identical to the symbolic notation of any $\alpha_n \in T$, i.e. with the left side of an inference rule created by an expert (α_n, β).

If two terms are selected by members of the current input n-tuple during the "fuzzification" process, it is possible to make up more n-tuples α_n* which are identical in their symbolic notations with the left sides of the inference rules (up to 2n of such α_n* may exist). Based on this assumption, it is possible through the "application of inference rules", to find the respective term $\beta \in \{Bj: j = 1,2,...,k\}$ for each α_n*. The n-tuple α_n*, as selected by measured or otherwise determined values of the current input n-tuple, unlike n-tuple $\alpha_n \in T$ created by an expert, has its origin in reality. It therefore also has a logic notation because it is the conjunction of the n-tuple of proposition type $x_0 \in Ai$, of which the non-zero truth value ($|x_0 \in Ai| = \mu_{Ai}(x_0) > 0$) selected the terms into the n-tuple α_n*.

If (in the logic notation) $\alpha_n* = (x_0 \in Ai) \wedge (c_0 \in Cu) \wedge ... \wedge (d_0 \in Dv)$, then (see the following part) $|\alpha_n*| = |(x_0 \in Ai) \wedge (c_0 \in Cu) \wedge ... \wedge (d_0 \in Dv)| = \min\{|(x_0 \in Ai)|, |(c_0 \in Cu)|,...,|d_0 \in Dv)|\} = \min\{\mu_{Ai}(x_0), \mu_{Cu}(c_0),..., \mu_{Dv}(d_0)\}$.

The truth value $|\alpha_n*|$ is the rate of justifiability of the selection of the α_n* n-tuple on the basis of the input data, which is information that was not available to the expert at the time they formulated the set of inference rules, and which was provided in reality through the input data. This information is used in the "results processing" phase. On the basis of the input data, if α_n* is the only selected n-tuple (i.e. $\mu_{Ai}(x_0) = \mu_{Cu}(c_0) = ... = \mu_{Dv}(d_0) = 1$), then $|\alpha_n*| = 1$. This means that the term β from the inference rule (α_n, β) is, where the n-tuples α_n* and α_n are identical from the viewpoint of symbolic notation, the only and the best continual result. For this reason, it may jump the "aggregation" phase and provide its $\mu_\beta = |\beta|$ for final processing in the "defuzzification" phase.

If α_n* is not the only n-tuple selected by the input data, $|\alpha_n*| < 1$, the term β is only a partial preliminary result. This means that its truth value, given by the function $\mu_\beta = |\beta|$, should be limited by the value $|\alpha_n*|$, as stated in the preceding section, to $\mu_\beta* = \min\{|\alpha_n*|, \mu_\beta\} = |\alpha_n* \wedge \beta| = |(\alpha_n*, \beta)|$. The transition from partial preliminary results to the overall preliminary result calls for the aggregation of all the partial results (i.e. $\mu_{\beta i}*$, $i = 1,2,...,r$) into a resulting μ_{agg}. This occurs in the "aggregation" phase (see Figure 2), where as a result of logical disjunction, the partial rules created in the preceding stages of the solution ($\alpha_{ni}*, \beta_i$), $i = 1,2,...,r$ are aggregated into proposition AGG = $(\alpha_{n1}*, \beta_1) \vee (\alpha_{n2}*, \beta_2) \vee ... \vee (\alpha_{nr}*, \beta_r)$. Then it applies: $\mu_{agg} = |AGG| = \max\{|(\alpha_{n1}*, \beta_1)|, |(\alpha_{n2}*, \beta_2)|,..., |(\alpha_{nr}*, \beta_r)|\} =$
$= \max\{\min\{|\alpha_{n1}*|, \mu_{\beta 1}\}, \min\{|\alpha_{n2}*|, \mu_{\beta 2}\},..., \min\{|\alpha_{nr}*|, \mu_{\beta r}\}\}$.

The created μ_{agg} function is the universal function of the basis values $p \in U_B$ of output linguistic function B with values in the range $0 \leq \mu_{agg}(p) \leq 1$. In the last phase of generating a solution, μ_{agg} is subjected to "defuzzification", the result of which is the required value p_0. This is the horizontal coordinate of the centre (centre of gravity) of the area limited from above by the course of function $\mu_{agg}(p)$, and which is limited from below by the axis of values "p" and from the left or right by values 0, or respectively 100. This is represented by the expression (1):

$$p_0 = \frac{\int_0^1 p \cdot \mu_{agg}(p)\,\mathrm{d}p}{\int_0^1 \mu_{agg}(p)\,\mathrm{d}p} \qquad (1)$$

The application of fuzzy logic to the evaluation of rating indices - procedures and results

It is necessary, on the basis of the values of the indices for the partial components of the quality of the entrepreneurial environment (i.e. index of corruption rejection (K), index of economic stability (E) and index of political stability (P)) for the selected countries, as published by specialized ratings agencies, to estimate the respective percentage values (see Table 1). The ratings attributed by agencies range from 0 to 100 points; the higher the value, the better the country's position in the given category. For the purposes of this study, all the data were expressed relatively within the interval ⟨0,1⟩; the higher the value, the "higher quality" position the country holds in the given category.

The algorithm enables the expert to, among other things, take into consideration the specifics of the relation various types of potential investors have to risk.

Table 1. Index values for corruption rejection, economic stability and political stability for selected countries in 2015 reflected in interval ⟨0,1⟩; 0 represents the worst evaluation and 1 the best evaluation.

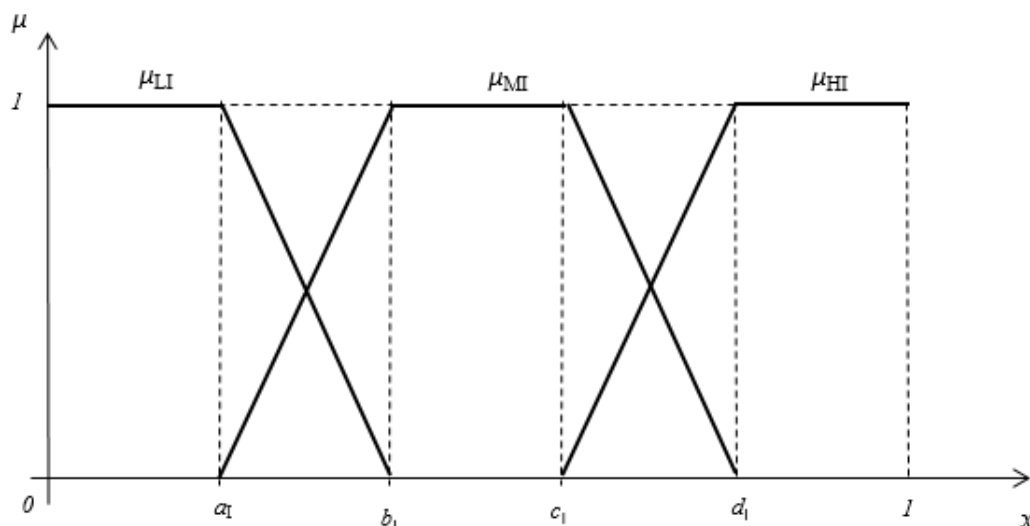| Country/Index	Index of corruption rejection (K) (interval ⟨0,1⟩)	Index of economic stability (E) (interval ⟨0,1⟩)	Index of political stability (P) (interval ⟨0,1⟩)
Czech Republic	0.56	0.73	0.88
China	0.37	0.52	0.7
Finland	0.9	0.73	0.86
Netherlands	0.87	0.75	0.85
Norway	0.89	0.71	0.9
Poland	0.62	0.69	0.81
Russia	0.29	0.51	0.52
Greece	0.46	0.53	0.6
Turkey	0.42	0.62	0.71

Sources: Corruption Perception Index, 2015; Country Rankings, 2015; Regional Political Risk Index, 2015; data processed by author

Generation of the fuzzy model

Three input linguistic variables are given: K (index of corruption rejection), E (economic stability), P (political stability) with value domains $U_K = U_E = U_P = ⟨0,1⟩$, of which the identified basis values are the numbers stated in the respective columns in Table 1. The task is to determine the respective basis values of the output linguistic variable O (quality of the entrepreneurial environment) in the value domain $U_O = ⟨0,100⟩$. To do this it is necessary to identify each of the linguistic variables by suitably selected terms

(fuzzy sets created on the respective domains of values U_I, I = K,E,P,O). In this case, the acceptable choice is fuzzy sets of ordered triplets I = (*LI, MI, HI*) = ({(x,μ_{LI}(x)): x ∈ U_I}, {(x,μ_{MI}(x)): x ∈ U_I}, {(x,μ_{HI}(x)): x ∈ U_I}), I = K,E,P,O, whereby the designation L represents the low value of the linguistic variable, M the mean value, H the high value, and which are defined by the trapezoidal functions of affiliation μ_{LI}(x), μ_{MI}(x) and μ_{HI}(x) (see Figure 1).

Figure 1. Courses of functions of affiliation to terms of linguistic variable I, for I = K,E,P,O

Source: Author

The following therefore apply:
(1) μ_{LI}(x) = 1 for 0 ≤ x ≤ a_I,
   μ_{LI}(x) = (b_I − x) / (b_I − a_I) for a_I ≤ x ≤ b_I,
   μ_{LI}(x) = 0 for x ≥ b_I

(2) μ_{MI}(x) = (x − a_I) / (b_I − a_I) for a_I ≤ x ≤ b_I,
   μ_{MI}(x) = 1 for b_I ≤ x ≤ c_I,
   μ_{MI}(x) = (d_I − x) / (d_I − c_I) for c_I ≤ x ≤ d_I,
   μ_{MI}(x) = 0 otherwise

(3) μ_{HI}(x) = 0 for 0 ≤ x ≤ c_I,
   μ_{HI}(x) = (x − c_I) / (d_I − c_I) for c_I ≤ x ≤ d_I,
   μ_{HI}(x) = 1 for x ≥ d_I

The distribution of the parameters a_I, b_I, c_I, d_I for various I = K,E,P along the horizontal axis of the diagram reflects the distribution of the basis values of these variables. In Table 1, where I = K, a total of 5 basis values are located under the limit of 0.6, unlike for I = P, where only one is under this limit. For this reason a_K < a_P. With regards to I = O, where the distribution is unknown and there is no reason to assume asymmetry, it is

therefore assumed that $a_0 = 20$, $b_0 = 40$, $c_0 = 60$, $d_0 = 80$. By making this choice of parameters for the functions of affiliation to the terms of the input linguistic variables we can take into consideration the structure of the measured or otherwise established data in the fuzzy model.

The next step in the generation of the fuzzy model for the assigned task is to draw up a set of inference rules of type ((J_1K,J_2E,J_3P), JO) for the allocation of the three output terms to the, in total, 27 ordered triplets of the input terms, where $J_1,J_2,J_3,J \in \{L,M,H\}$. The basic strategy here is the selection of *JO*, in which the ordered triplet (J_1K,J_2E,J_3P) prevails in *J*. If none of them prevails, *MO* is chosen. This selection strategy assigns *MO* to, in total, thirteen ordered triplets of input terms; *LO* or respectively *HO* are assigned seven of the remaining cases each (rules made up on the basis of the strategy stated in Table 2). By shifting some of the assignments to the right i.e. from *LO* to *MO* or *HO*, or from *MO* to *HO*, it is possible to compensate, to a certain degree, an investor's excessive fear of risk. Likewise, a shift in the opposite direction (from *MO* to *LO* or from *HO* to *MO* or *LO*) discourages investors who have an indifferent attitude to risk from taking excessive risks.

Table 2. Formulation of the decision-making rules (vague value L marks "low quality", M "mean quality" and H "high quality"

LLL→L	LLH→L	LMH→M	MMM→M	MLL→L	MHM→M	HHH→H	HLH→H	HHM→H
LLM→L	LHL→L	LMM→M	MLM→M	MLH→M	MHH→H	HLL→L	HMM→M	HLM→M
LML→L	LHM→M	LHH→H	MML→M	MMH→M	MHL→M	HHL→H	HMH→H	HML →M

Source: Author

Fuzzy model algorithm for generating a solution to a task

The phases of the fuzzy model algorithm for generating a solution to a task are shown in the following figure:

Figure 2. Scheme of a fuzzy model algorithm for solving a task
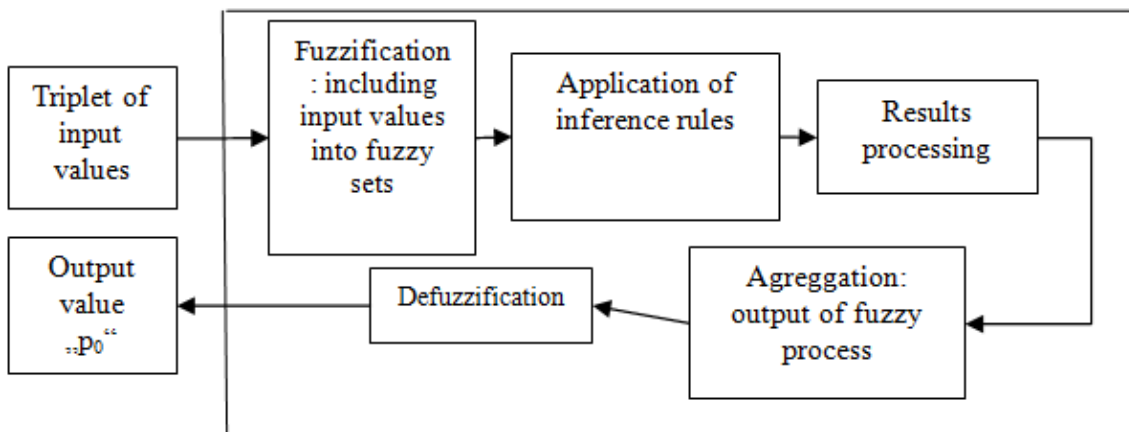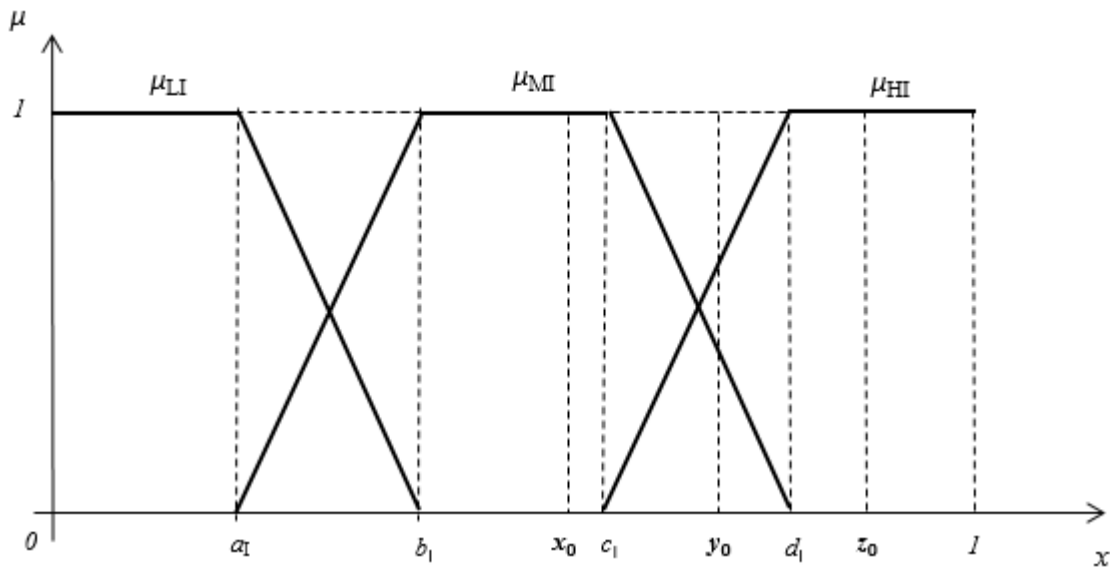

Source: Author

This can best be explained by constructing the parameter p_0 for the Czech Republic. For the purpose of simplifying the respective calculations, the differences in the distribution of the values of the individual indices was ignored (for each of them it is assumed that the parameters for the functions of affiliation to the terms are: a = 0.2, b = 0.4, c = 0.6, d = 0.8).

The ordered triplet of the input basis values (x_0, y_0, z_0), $x_0 \in K$, $y_0 \in E$, $z_0 \in P$ is triplet (0.56, 0.73, 0.88). The inclusion thereof into the respective terms is presented in Figure 3.

Figure 3. Symbolic representation of the affiliation of the input values to the terms

Source: Author

It is evident that the following apply (see formulae for calculations under Figure 1):

$0.56 \in MK$ with the degree of truth $|0.56 \in MK| = \mu_{MK}(0.56) = 1$;

$0.73 \in ME$ with the degree of truth $|0.73 \in ME| = \mu_{ME}(0.73) = (0.8 - 0.73) / 0.2 = 0.35$;

$0.73 \in HE$ with the degree of truth $|0.73 \in HE| = \mu_{HE}(0.73) = (0.73 - 0.6) / 0.2 = 0.65$;

$0.88 \in HP$ with the degree of truth $|0.88 \in HP| = \mu_{HP}(0.88) = 1$.

With this, the fuzzification process is completed, whereby the input values for the selected ordered triplets (0.56, 0.73, 0.88) were assigned in symbolic notation as $\alpha_{MMH} = (MK,ME,HP)$ and $\alpha_{MHH} = (MK,HE,HP)$, or in logic notation as $\alpha_{MMH}^* = (0.56 \in MK) \wedge (0.73 \in ME) \wedge (0.88 \in HP)$, $|\alpha_{MMH}^*| = \min\{1, 0.35, 1\} = 0.35$; $\alpha_{MHH}^* = (0.56 \in MK) \wedge (0.73 \in HE) \wedge (0.88 \in HP)$, $|\alpha_{MMH}^*| = \min\{1, 0.65, 1\} = 0.65$.

By applying the inference rules to the symbolic notation of the ordered triplets, in accordance with rules $((MK,ME,HP), MO)$ and $((MK,HE,HP), HO)$, the MO and HO outputs were determined. It then follows that:
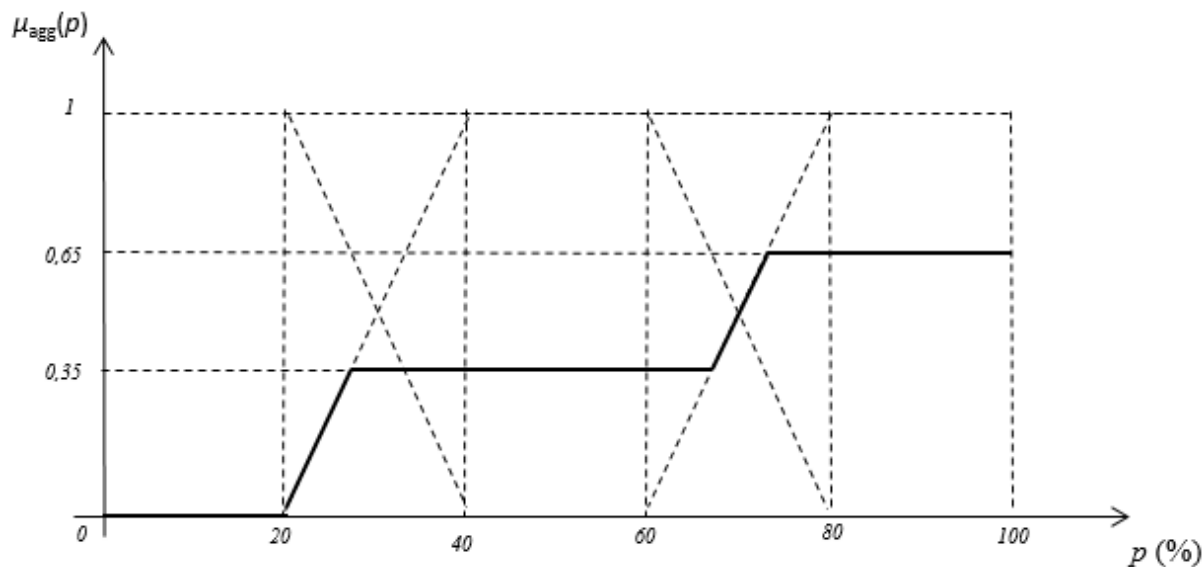
$AGG = (\alpha_{MMH}^*, MO) \vee (\alpha_{MHH}^*, HO)$ and

$\mu_{agg} = |AGG| = \max\{\min\{|\alpha_{MMH}^*|, \mu_{MO}\}, \min\{|\alpha_{MHH}^*|, \mu_{HO}\}\} =$

= max{min{0.35, μ_{MO}}, min{0.65, μ_{HO}}}.

The course of the μ_{agg} function is presented in Figure 4.

Figure 4. Graph of function μ_{agg}

Source: Author

On the basis of Figure 4, the value p_0 is determined as being (0.35·(30+40+50+60)+0.5·70+0.65·(80+90+100)) / (4·0.35+0.5+3·0.65) = 71 % by means of the numerical approximation of the values of the integrals in the formula for the calculation of the horizontal coordinate of the position of the centre of gravity at the end of the methodological part.

The resulting "p_0" values for the selected countries are summarised in Table 3.

Table 3. The "p_0" values for the quality of the entrepreneurial environment indices expressed in percent

Country	Quality Index „p_0" in %
Czech Republic	71
China	50
Finland	86
Netherlands	86
Norway	85
Poland	60
Russia	50
Greece	50
Turkey	54

Source: Author

Discussion of the results from the viewpoint of the investment decision

The preceding section quantifies the estimated parameters for the quality of the entrepreneurial environment (see Table 3) on the basis of the input data published by three selected ratings agencies (see Table 1) and based on the application of fuzzy logic. The stated results approximate the input rating variables on the basis of a fuzzy model algorithm, which enabled the opinions and experiences of experts (managers) to be taken into consideration with regards to the generation of a solution subject to the needs and character of an investor. The resulting "p_0" value, with regards to the necessity to make a decision on an investment, for example in the Czech Republic, may be interpreted as the overall parameter for determining the quality of the entrepreneurial environment for the selected areas of evaluation (it is expressed in percent; the higher the value, the higher the quality of the entrepreneurial environment).

What has not been discussed, and which is also important to take into consideration at this point, is the existence of uncertainty contained in the ratings data (Munda et al. 1995). This uncertainty is linked to the methodology for deriving the ratings data. The methodology utilizes vague procedures based on qualitative evaluations. For example, the modified data used in the analysis for the evaluation of the corruption perception index are based on the rate of perceived corruption in the public sector by those who can come/came into contact with it. In order to achieve the maximum explanatory/predictive value, it is necessary to use more surveys that harness different methodologies for collecting and evaluating data. This uncertainty, for example, from the psychological standpoint of an investor to risk, is reflected in the construction of the function of affiliation μ_x and the formulation of the strategic decision-making rules based on the opinion of the expert and on the "credibility" of initial ratings evaluation.

It is for this very reason that statistical methods for processing uncertain data and/or problems involving sociologically-psychological factors do not have fundamental substantiation. Expressing the index for the quality of the entrepreneurial environment for the concerned managerial task in terms of, for example, the geometrical (X_G) or harmonic mean (X_H) (see Table 4), provides an identical or similar evaluation to the index for the quality of the entrepreneurial environment by "p_0" using fuzzy logic. However, it is impossible to justify choosing the method of statistical averaging because the principles of the procedures for doing so do not take into consideration the basic characteristics of the task to be solved.

Table 4. Evaluation of selected indices of ratings agencies and the approximation of these values using the parameters for the quality of the entrepreneurial environment

Country/Index	Index of corruption rejection (K) (interval $\langle 0,1\rangle$)	Index of economic stability (E) (interval $\langle 0,1\rangle$)	Index of political stability (P) (interval $\langle 0,1\rangle$)	Index of quality „po" (interval $\langle 0,1\rangle$)	Geometric average of ratings X_G	Harmonic average X_H
Czech Republic	0.56	0.73	0.88	**0.71**	0.71	0.7
China	0.37	0.52	0.7	**0.50**	0.51	0.49
Finland	0.9	0.73	0.86	**0.86**	0.82	0.82
Netherlands	0.87	0.75	0.85	**0.86**	0.82	0.82
Norway	0.89	0.71	0.9	**0.85**	0.83	0.82
Poland	0.62	0.69	0.81	**0.60**	0.7	0.7
Russia	0.29	0.51	0.52	**0.50**	0.4	0.4
Greece	0.46	0.53	0.6	**0.50**	0.5	0.52
Turkey	0.42	0.62	0.71	**0.54**	0.57	0.56

Source: Author

Summary and conclusion

In complex situations that are characterized by unspecified influences and which result in uncertainty, people usually follow the normative rules for a particular situation, or act on the basis of their knowledge and experience, or both. However, different circumstances may arise if a situation is uncertain or the choice of the relevant rule is not unambiguous. This reflects the fact that the concepts and procedures on which rules are usually based are also often vague and ambiguous. A typical example is the area of managerial decision-making with regards to indefinite and future situations burdened by uncertainty. Managers therefore use a number of qualitative and quantitative procedures to minimize that uncertainty and risks.

This contribution utilizes fuzzy logic to extend the standard ways in which to quantify entrepreneurial risk. It enables the uncertainty and vagueness of sociological and psychological factors which occur in managerial tasks, including the uncertainty of the input data, to be comprehensively described. In this study, the fuzzy method is applied to a practical managerial task in which an investment consultant, based on the values of selected indices of three world ratings agencies for selected countries in Europe and Asia, evaluates the quality of the prevailing entrepreneurial environment, whilst taking into consideration the relationship of a particular investor to risk.

The partial components of the ratings evaluations are processed in the following phases using the fuzzy model algorithm presented in Figure 2: ordered triplets of input values are included into fuzzy sets to which inference rules are applied; the partial results are subsequently processed and aggregated within the output fuzzy process and

transformed into resulting values. The resulting values can be interpreted as parameters for determining the quality of the entrepreneurial environment in selected states.

The application of fuzzy logic is discussed and evaluated in comparison to the statistical approach based on the method of averaging. These procedures provide identical or similar results to the fuzzy logic approach. However, it is impossible to justify choosing the method of statistical averaging because the principles of the procedures for doing so do not take into consideration the basic characteristics of the task to be solved.

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