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TRENDS OF USING ARTIFICIAL INTELLIGENCE IN MEASURING INNOVATION POTENTIAL

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Abstract
The field of academic research on corporate sustainability management has gained significant sophistication since the economic growth has been associated with innovation. In this paper, we are to show our research project that aims to build an artificial intelligence-based neuro-fuzzy inference system to be able to approximate company's innovation performance, thus the sustainability innovation potential. For this we used an empirical sample of Hungarian processing industry's large companies and built an adaptive neuro fuzzy inference system.

Keywords
process mapping, production logistics, process improvements, shipyard industry.

Introduction

The complementary technical terms of 'innovation' and 'sustainability' are far from being newcomers in our contemporary global discourse. Already in the 1970s and 1980s, these opposite, but interrelated concepts were introduced in discussions related to the global extension of economy, the natural limits to economic growth, the implosive reduction of markets, ever-increasing prices and competition between economic actors. However, during this period, social and environmental topics were less intensely discussed. The situation changed in the last decade of the 20th century, due mainly to the Brundtland Report [1], which initiated a creative debate on topics such as production (or the transformation of resources), innovation processes, and sustainability [2]. Lately, a great number specialists (including [3–5]) have become greatly interested in the topics of sustainability as well as social and environmental awareness. It has also become clear that, additionally to innovation, sustainable development may also represent a significant competitive edge for companies. According to this new perspective on growth, both financial profitability, seen in a wider context, and long-term sustainable initiatives have to involve environmental and social values as well [4, 6]. Thus, companies had to face the challenge of reforming their traditional structures and introducing policies focused on sustainability in their economic approaches [4, 7, 8]. Nevertheless, the specialist analysis of sustainability in the corporate context can be viewed as a quite new development, along with its focus on the global environment and the various levels of organizational structure (i.e. particular individuals, organizational groups and subgroups, the organizational macro-level, and larger organizational clusters). In other words, it is a relatively new field of studies, related to, but not synonymous with older, related fields of study, e.g., the study of organization behaviour, environmental economics, corporate strategy and the management of change and innovation processes.

Theoretical framework and literature review

Sustainable innovation

According to Austrian political economist Joseph Schumpeter, innovation may be characterized as the "realization of new combinations" [9]. His classic definition was subsequently further developed by other authors focusing on economic aspects of this encompassing category [10], being even considered the growth engine of society as a whole [11]. Some researchers have inventoried more than 40 alternative determinations of the same concept [12].

How do sustainability and innovation tie into each other on the organizational level? In order to answer this fundamental question, one has to identify the relatively recent way in which organizations practice innovation in recent years, subsumed under the technical term of 'sustainable innovation' [13, 14], a category widely recognized as significant by business specialists, strategic and innovation managers, as well as contemporary economists [2], many of them considering it the determinant factor for obtaining long-term business value [15, 16].

Taking their starting point in Martin Heidegger's technological criticism, co-authors Iñigo and Albareda [2] came up with a new ontology for sustainable innovation in organizations, identifying its following core elements:

1. The material input of sustainable development, the operational element, i.e. the material cause.
2. The collaborative component, associated with the sustainable innovation-generating form, i.e. the formal cause.
3. The organizational element, centred on institutional development, as the achievement of processes inspired by the idea of sustainable development or due to the fact that the company in engaged in sustainable development, i.e. the efficient cause.
4. The instrumental aspect is related to the fact that sustainable development may also be the method for attaining the proposed objective, associated with the envisioned consequence, i.e. the final cause.
5. Finally, the component that probes into sustainable development in the framework of a superior system development and contributes to the spread of a novel paradigm of sustainable development, i.e. the holistic element (cf. the Heideggerian Gestell, or 'en-framing').

Co-authors Delmas and Pekovic [17] view sustainable (or environmental) innovation as lying in developmental processes and concrete products capable of lessesing the load on the environment [18–21]. Thus, sustainable innovation confronts organizations with a hitherto unknown provocation, since it imposes the criterion of increasing company profits while also not ignoring the organization's social responsibility [22]. Innovations related to processes and products, marketing strategies and organizational structures can only be viewed as sustainable if they are capable of protecting our natural environment [23]. According to a high number of experts [24–31], the problems of sustainable development may be handled by finding solutions in the area of innovation. The long-term sustainability of our products and services may be increased through the use of current scientific achievements and new methods of technology management [32].

The feature that distinguishes innovation from invention consists, according to Przychodzen & Przychodzen's review of the existing scholarly literature [33], by the application of innovative ideas, practices, processes and products [24]. So what is the additional characteristic of sustainable innovation in this wider context? In addition to the aforementioned features, the innovation also has to present specific social and environmental advantages. Its use of non-renewable resources has to show higher efficiency and lead to greater coherence of society, as well as reduce environmental pollution [34], simultaneously maintaining an economic aspect and increasing profit [35].

Assessing the potential for innovative development

Generally, there are two aspects of assessing innovation potential and performance, related, on the one hand, to variable complexity as well as to measurement and interpretation complexity in inferences, and on the other hand, to the complexity dimension in the inference pattern that is used, i.e. the way in which it can be interpreted through straightforward linear functions or through more complicated, nonlinear mapping. On the basis of these considerations, I have devised the following methods:

1. The analysis of simple index numbers.
2. Partition coefficient-based horizontal/vertical investigation.
3. Correlation method-based calculus (regression) and the method of standard deviation.
4. Further developed regression methods (manual and path models), canonical correlation, and latent variable methods (principal component, multidimensional scaling, correspondence methods).
5. AI-based models (e.g. neural networks, fuzzy systems).

As seen in the figure above, there is a great number of criteria for selecting between assessment approaches. In this choice process, the basic position for assessing the capacity for innovation and the specific activities to be assessed are indifferent variables. Modernization can consist both in slight alterations of products already on the market or currently developed and in the creation of different products, identifying additional suppliers and market, as well as even in rationalizing the company at the macro-level. As for the processes themselves, these can range from the achievement of new know-how all the way to solving everyday life issues and to innovative solutions for experimenting with and assessing newly implemented methods and even appraising the developmental approach. Irrespective of the chosen method, innovation is generally measurable according to the set of variables. An essential differentiating criterion to be assessed lies in the complexity grade that is characteristic for the innovation mechanism. This is influenced by the above-stated two factors. Nevertheless, an adequate choice cannot be made solely on their basis [36]. The processes included in the first group are conveniently characterized relying on simple index numbers and via numerical indicators. In another situation, it may be more difficult to characterize innovations via indexes. The process may be of such complexity and stochasticism that the data prevents the transformation to functions and numeric variables.

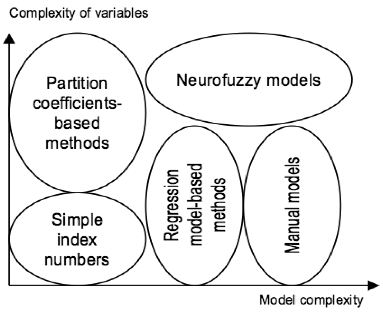

Fig. 1. Assessment models of innovation achievement.

One should also contemplate the level for assessing the possibilities of innovation. This can be done either on the micro or the meso/macro level, for specific (economic and geographical) regions and individual locations. The interconnections of innovation also influence our chosen method. The question is whether the innovation may be isolated from more encompassing developments and their characteristic correlations. The methodological choice is also influenced by the character and the level of the potential abstraction of the analysis variables. The following abstraction levels may thus be defined: simple abstraction of specific factors influencing innovation processes, abstraction of the individual factors depending on the contextual framework, simultaneously complex and individual abstraction, as well as complex abstraction process with complex innovation. The assessment of these factors may be followed by the adequate methodological choice, i.e. index number generation via simple methods, ratio-based simple analysis, correlation- and regression-model based traditional methods of statistics, as well as manual path models – the strategies hitherto used by traditional investigations for assessing the potential for innovative development.

Conceptualizing the research problem

The measurement of the sustainability characteristic for innovation processes and achievements is a quite complex problem even at the current state of research. Several popular methods fail as the scholars investigating the topic have to subject themselves to limiting conditions while constructing their models. Traditional modelling processes are often not adequate for issues such as target function's the highly complex character, i.e. our research task when the function to be analysed with respect to the optimum or other specific points. It may be possible that the only conclusions that can be established are of an estimative character if a superior level of statistical error is associated with an inferior level of significance. Generally, the stochastic perspective is the source of several difficulties and limitations for social research. The issue under investigation is often difficult to be stated in terms of distinctly perceptible variables. The choice of both the grading instrument and the evaluation strategy may produce disorientation, biases and problems related to handling the function of the outliers. Among the relevant topics of present analyses, an often-encountered limiting circumstance consists in system information of the subjective kind, since the use of quantity principles represents a general premise of traditional approaches to system modelling. Nevertheless, these objective perspectives of quantity are quite rare in social research. Hence, researchers usually turn the assessment principles based on quality into quantity-centred perspective. But can we be sure that this automatically grants us the desired objective criterion? In fact, the system information of social research, as well as of economy as a social science, is of a subjective nature, because our human experience intrinsically and without exceptions [37] has the very same character. Irrespective of what positivism teaches, it is highly doubtful whether the social scientist can ultimately be objective in his approach. However, if the system information we have to work with has a subjective nature, but the method we use need the objective approach (as the requirements of scientific positivism also dictate), then we have to somehow objectivate our subjective data – or else find a method for treating system information dependent on value assessments of the subjective kind.

The demands posed by linearity are particularly strong here, as the majority of social scientific models use linear regression. Economic relations are mostly nonlinear in their parameters and/or variables. The scientist thus has to turn the nonlinear conditions studied into a model that is linear (sometimes even accepting the inevitable biases), because the requirements for the prediction of the specifications for such models of the nonlinear kind may be impossible to satisfy, in which cases the variables have to be determined again.

In the regression model, homodestacity has to each probability variable. Thus, each variable will have an identical, finite variance of $\sigma 2$, and the probability distribution's standard deviation with the target variable will be identical, regardless of the explanatory variables. Hence, the deviation variables' covariance matrix will be of the scalar kind, with the identical $\sigma 2$ values in the main diagonal. The tests for homodestacity will be the Goldfeld-Quandt, the Breusch-Pagan and the White tests.

Our model's analytical variables have to be mutually independent, i.e. no variable may be reproducible via linear combination of other variables. Actually, real instances of such systems, based on stochastic principles, for which the validity of specific criteria does not automatically preclude the possibility of others, are rare. Furthermore, there are numerous limiting criteria to be taken into consideration, contained in most manuals on statistics. For these reasons, the scientific approach to the potential of innovation is itself in need on innovative, AI-based approaches.

As shown in the previous chapter, measuring innovation capability on micro level has a wide methodological apparatus, however these methods mostly rely on classical statistical system modelling basis, which has many limitations and unrealistic conditions which are very hard to satisfy in social sciences (e.g. linearity, normality, homoscedasticity) [38, 39]. To dissolve this methodological gap of stability and plasticity, exactitude (arithmetical formalism) and significance, precision and flexibility artificial intelligence-based methods seems to be an answer such as fuzzy-logic based modelling and neural network or even their synergic combination [40].

There are more and more good examples of applications of fuzzy logic can be found in literature, but many of them aim to measure macro level innovation performance of a region, country [41–43]. There are much fewer evidences on corporate innovation measurement, however they are mainly focus either on innovation process or a corporate functional innovation field [44–47].

Application of neural networks for quantification of innovation activity is much narrower [48–50] however the method is absolutely suitable for such problems as shown in literature [39, 51–53].

The combination of the two artificial intelligence methods would result a precise and flexible, however a very stable and arrhythmically well formalised, which is fuzzy and exact at the same time [54–56].

In this paper we are to show the effectivity of this combination of the two methods. This has its antecedents as our team has been dealing with this methodological problem long ago [39, 57, 58]. This current research is the precious and a more detailed elaboration of our previous model [59] with a different approach. This will be shown in the following chapter.

Methodology

Sample and variables

In order to run our model random sample had to be established. In order to reach an interpretable sample size, the paper-based questionnaires had been sent to every item of the population, addressed to the head of R&D or innovation department. Thus, the returned questionnaires have formed our sample as follows:

- Population: Large processing industry companies (250 or more employees), located in Hungary ($N = 207$).
- Sample: Significant both from the perspective of sub-sectorial (Mann-Whitney U-test; $p = 0.197$) and geographical (NUTS-2) distribution (Mann-Whitney U-test; $p = 0.329$). $n = 100$ (97 without any missing data).

Table 1
Sample distributions.

Location	[%]	**Sub-sectors**	[%]
Budapest	21	Food and beverages	13
Southern Great Plain	16	Tabaco	1
Southern Transdanubia	2	Textile	1
Northern Great Plain	8	Paper, printing	6
Northern Hungary	15	Chemicals, pharmaceutical	8
Central Transdanubia	17	Plastic	4
Central Hungary	10	Mineral products	9
Western Transdanubia	11	Metal	12
		IT	12
Employees	%	Machinery	15
250–300	23	Vehicle industry	16
300–499	29	Energy, water	3
500–999	20		
1000–1999	19		
2000+	9		

Table 2
Input vectors and their aggregation by factor analysis.

Grouping variables	Factors	KMO	Bartlett p	Σ variance
Motivation		0.749	0.000	69.625
Socialization	Culture	0.840	0.000	71.818
	Age of experts			
Strategy		0.893	0.000	75.332
Diffusion	Stakeholder cooperation	0.741	0.000	63.176
	Seconder information sources			
	External cooperation			
Information	Internal information infrastructure	0.728	0.000	68.112
	External information infrastructure			
Resources	Intangible resources	0.604	0.000	68.401
	Material resources			
Technology	Technology modernity	0.714	0.000	65.085
	Push technologies			
	Pull technologies			
Results	Objective results	0.576	0.000	55.468
	Subjective results			

In this sense the sample represents 46.11% of the total population.

Innovation potential is estimated by 75 measured (on 1–6 Likert scale with 3–3 linguistic statements, showing the agreement with the statement by degree). Specific variables of the model were included into 9 grouping variables and divided into 16 factor elements as follows: motivation, socialization (the specific culture of the organization and the age of the experts), adaptation, strategy, diffusion (stakeholder cooperation, secondary information retrieval, external cooperation), information (internal information infrastructure, external information infrastructure), resources (intangible resources, material resources), technology (technological modernity, push technologies, pull technologies), results (objective, subjective) and action (internal push innovation, external pull innovation) as dependent variables. Our variables are thus in accordance with the Frascati and Oslo Manual.

The outline of a possible solution

The most important step in developing the intelligent system for approximation of sustainable innovation is to identify according to a priory information how will be an innovation resulted in accordance with the company's possibilities and limitations. It cannot be decided in advance, but after analyzing the data on hand, an accurate estimation can be given. An inference system can easily and automatically solve this issue. We already have the variables for the model that have an essential role in the innovation process as described above. The number of cases and the number of variables, such as their variance is suitable for the model. A fuzzy inference system provides a simple and good solution. The aim of this research is to show that such a fuzzy inference system (FIS) is able to accurately approximate the sustainable innovative performance of a company. The problem and the set of variables (16 input linguistic variables) consists a multivariable inference system with few outputs (3 variables).

As it can be concluded in accordance with the previously described coincidences, a classic fuzzy system cannot be applied as linguistic variables are known and we can also determine the linguistic values associated with each variable (we will usually handle 2–6 language values). The problem is that we have a (statistically) good sample with enough cases and variables, but the fuzzy membership functions are unknown. They are not explicitly available. However, the fuzzy inference sets would be very suitable to draw conclusions in the determination of the sustainability of the innovation potential – not just according to our experiences [38, 39, 60], but it is also verified in the literate [51, 52, 57, 61–65] that a FIS would be very useful in the approximation.

FIS is a superb inference system with crisp internal information, outstandingly effective inference method, but it is static. Neural networks in the same time are able to learn and may exploit and algorithmize the benefits of the everyday human thinking (soft calculation – fuzzy logic) and the learning and adaptation abilities of the neural systems – the synergy between the mathematized everyday human thinking and classical mathematics. However – like a black box - does not reveal the structure of the inference mechanism, but their approximation performance is outstanding. The combination of the two would be the best solutions for the problem described above.

The idea of fuzzy systems came from Lotfi A. Zadeh – professor of mathematics at Berkeley University – at the 1960s. In the '80s, Sugeno suggested, that on the conclusion side of the rules instead of sets functions should include [66]. This development is very important for our problem.

Neuro-fuzzy systems appeared in the 1980's and structurally appeared in 6 variants, two of them spread more widely [57]:

1. Cooperative system in which the basic fuzzy system is tuned with neural network.
2. A single fuzzy inference procedure tailored to a neural network, which contains "fuzzy neurons" and fuzzy weights. The structure of the original fuzzy system can be recognized from the network topology.

For our problem – as explained above – the second method fits the best. Such a method is the adaptive neuro fuzzy inference system (ANFIS). In order to make the ANFIS applicable for the generalized system, we should examine whether it is suitable for a simplified model of the problem.

ANFIS is a 5-layer neural network:

- The first layer consists of the inputs and the associated linguistical variables and values and the accordingly connectivity neurons. Each neuron receives signal from a single input.
- In the second layer, elements of the first layer are associated with the inferential rules. Here appears the conditions of inference rules and the AND/OR connections between premise elements.
- The third layer ensures their normalization (invisible).
- The fourth layer determines the consequences of the rules. Here a zero-order Takagi-Sugeno type inference system will be applied.
- The fifth layer contains only one neuron which determines the final output [48, 51].

In our investigations we discovered what linguistic variables play a role in the approximation of innovation with artificial intelligence (neurofuzzy network). We assigned linguistic values to these linguistic variables denoted by 16 input and 3 output variables. Output variables are the resulted decision variables are as follows:

- (Discrete) sustainable innovation potential
- (Continuous) internal push innovation potential
- (Continuous) market pull innovation potential.

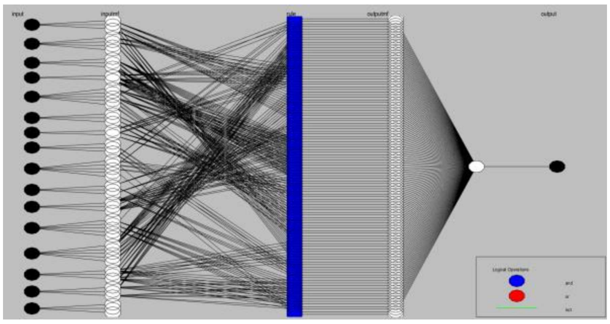

Fig. 2. ANFIS for approximating sustainable innovation potential.

The following table summarizes the variables and their values briefly.

Table 3
Linguistic variables and their values.

Inputs	Low	Med.	Med.2	Med.3	High
Motivation	x	x	x		x
Strategy	x		x		x
Culture	x	x			x
Technology modernity	x		x		x
Stakeholder cooperation	x		x		x
Seconder information sources	x	x			x
External cooperation	x				x
Objective results	x	x			x
Subjective results	x	x	x		x
Intangible resources	x	x			x
Material resources	x	x			x
Internal information infrastructure	x	x			x
External information infrastructure	x	x	x	x	x
Age of experts	x		x	x	x
Push technologies	x	x	x		x
Pull technologies	x	x	x		x
Outputs					
(Discrete) sustainable innovation potential					
(Continuous) internal push innovation potential					
(Continuous) market pull innovation potential					

Output variables do not have sets due to Sugeno. Here, all variables will have as many values as many inference rules they have (e.g. the first output has 113 values). In this paper only the first discrete model is shown, others are similar.

Innovation potential

Innovation Potential (IP) has a discrete scale (1, ..., 5). For convenient handling, this had been converted to [0; 1] intervals based on the following formula:

$$\mathrm{IP}' = \mathrm{IP} \cdot 0.2.$$

During processing, this must be converted back and rounded to integer value according to the following formula:

$$\mathrm{IP} = \mathrm{round}\left(\frac{\mathrm{IP}'}{0.2}\right).$$

The initial neuro-fuzzy model (inference rules)

To the fuzzy system simple IF ... THEN ... rules are associated.

Three models were generated but as mentioned only the first one is presented in detail in this paper. For this we specify conclusions of the inference rules (antecedents).

Table 4
Antecedents of the fuzzy rules.

1	Motivation	Strategy	Culture	Technology modernity	Stakeholder cooperation	Seconder information sources	External cooperation	Objective results	Subjective results	Intangible resources	Material resources	Internal information infrastructure	External information infrastructure	Age of experts	Push technologies	Pull technologies
2					LOW				LOW							
3					HIGH				LOW							
4					LOW				HIGH							
5					HIGH				HIGH							
6														LOW	LOW	LOW
7														HIGH	LOW	LOW
8														LOW	LOW	HIGH
9														HIGH	LOW	HIGH
10														LOW	MEDIUM	LOW
11														HIGH	MEDIUM	LOW
12														LOW	MEDIUM	HIGH
13														HIGH	MEDIUM	HIGH
14														LOW	HIGH	LOW
15														HIGH	HIGH	LOW
16														LOW	HIGH	HIGH
17														HIGH	HIGH	HIGH
18		LOW		LOW			LOW									
19		HIGH		LOW			LOW									
20		LOW		LOW			HIGH									
21		HIGH		LOW			HIGH									
22		LOW		HIGH			LOW									
23		HIGH		HIGH			LOW									
24		LOW		HIGH			HIGH									
25		HIGH		HIGH			HIGH									
26	LOW													LOW		
27	LOW													MEDIUM2		
28	LOW													MEDIUM3		
29	LOW													MEDIUM4		
30	LOW													HIGH		
31	MEDIUM													LOW		
32	MEDIUM													MEDIUM2		
33	MEDIUM													MEDIUM3		
34	MEDIUM													MEDIUM4		
35	MEDIUM													HIGH		
36	HIGH													LOW		
37	HIGH													MEDIUM2		
38	HIGH													MEDIUM3		
39	HIGH													MEDIUM4		
40	HIGH													HIGH		
41										LOW		LOW				
42										LOW		MEDIUM				
43										LOW		HIGH				
44										HIGH		LOW				
45										HIGH		MEDIUM				
46										HIGH		HIGH				
47			LOW	LOW	LOW							LOW				
48			LOW	HIGH	LOW							LOW				
49			LOW	LOW	LOW							HIGH				
50			LOW	HIGH	LOW							HIGH				
51			LOW	LOW	HIGH							LOW				
52			LOW	HIGH	HIGH							LOW				
53			LOW	LOW	HIGH							HIGH				
54			LOW	HIGH	HIGH							HIGH				
55			HIGH	LOW	LOW							LOW				
56			HIGH	HIGH	LOW							LOW				
57			HIGH	LOW	LOW							HIGH				
58			HIGH	HIGH	LOW							HIGH				
59			HIGH	LOW	HIGH							LOW				
60			HIGH	HIGH	HIGH							LOW				
61			HIGH	LOW	HIGH							HIGH				
62			HIGH	HIGH	HIGH							HIGH				
63							LOW		LOW							
64							LOW		MEDIUM							
65							LOW		HIGH							
66							HIGH		LOW							
67							HIGH		MEDIUM							
68							HIGH		HIGH							
69			LOW			LOW										
70			MEDIUM			LOW										
71			HIGH			LOW										
72			LOW			MEDIUM										
73			MEDIUM			MEDIUM										
74			HIGH			MEDIUM										
75			LOW			HIGH										
76			MEDIUM			HIGH										
77			HIGH			HIGH										
78		LOW			LOW											
79		LOW			MEDIUM2											
80		LOW			MEDIUM3											
81		LOW			HIGH											
82		HIGH			LOW											
83		HIGH			MEDIUM2											
84		HIGH			MEDIUM3											
85		HIGH			HIGH											
86	LOW														LOW	
87	LOW														MEDIUM	
88	LOW														HIGH	
89	MEDIUM														LOW	
90	MEDIUM														MEDIUM	
91	MEDIUM														HIGH	
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106													MEDIUM		HIGH	LOW
107													MEDIUM		LOW	HIGH
108													MEDIUM		HIGH	HIGH
109													HIGH		LOW	LOW
110													HIGH		HIGH	LOW
111													HIGH		LOW	HIGH
112													HIGH		HIGH	HIGH
113									LOW							
114									HIGH							

Elaborating the solution of approximating sustainable innovation potential

For the chapter of Methodology, it can be clearly seen, that the problem-solving consist of several steps.

1. Step: Based on the specific linguistic variables and the basic inference rules, an initial system is built up which will be the starting point for our neural network.
2. Remark: the application would be able to generate an initial FIS, but the available data should be used for a more accurate and faster learning (training) process.
3. Step: Using the learning data, the ANFIS is being learnt to generate the FIS.
4. Step: The resulted FIS now can be used for in concrete cases for decision-making.
5. To solve the specific task, we used the MatLab application.

Building up the neuro-fuzzy model

In the first step the system is built on the basis of its structure. The following block diagrams show this structure.

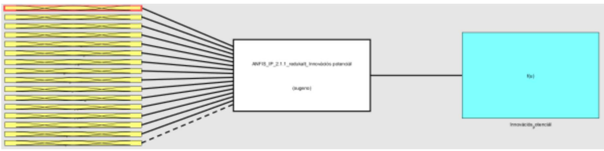

Fig. 3. The external structure of the system.

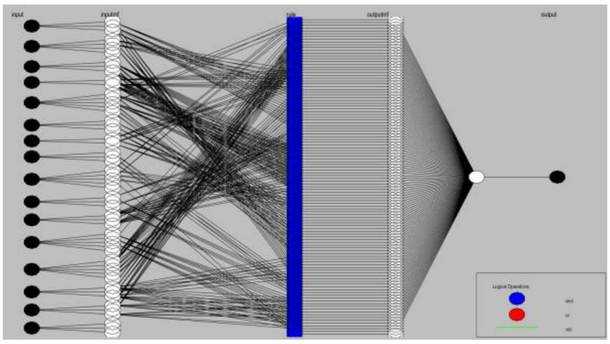

Fig. 4. The ANFIS of the problem.

Using the sample data of the data from the questionnaire survey the learning and control samples were created by randomly splitting the sample in half. A threshold subsample was also created and added to the database as control.

The ANFIS module of MatLab was used for training. As optimizing method, we used the hybrid option. The number of epochs was set to 150, but the outcome resulted in less than 100 steps.

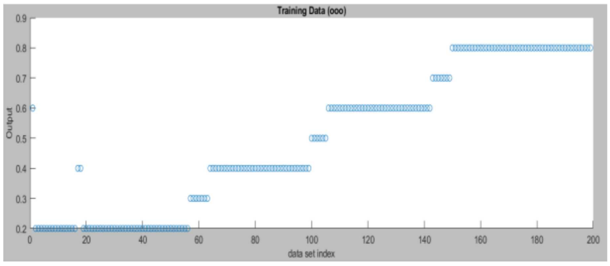

Fig. 5. Training data.

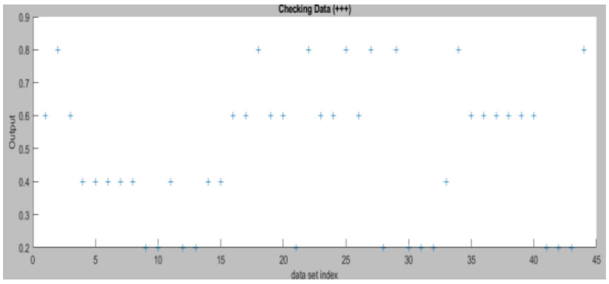

Fig. 6. Control data.

Training the model

The second step is training. Based on the set parameters, the training process has been started. The result converged during the training process according to the figure below.

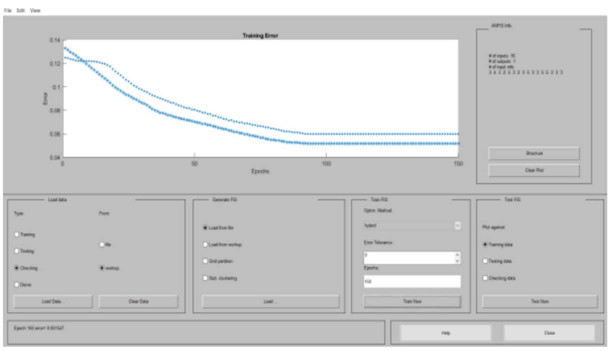

Fig. 7. Training process.

Errors of the final solution:

Minimal training RMSE = 0.052217

Minimal checking RMSE = 0.056194

The third step is controlling the results on two specified and randomly selected cases. In case 1 the company's innovation potential resulted to be 2 (low innovation potential on 1–5 scale) and in case 2 it resulted in 4 (higher innovation potential on 1–5 scale). The values of the resulted FIS after the training is shown in table below.

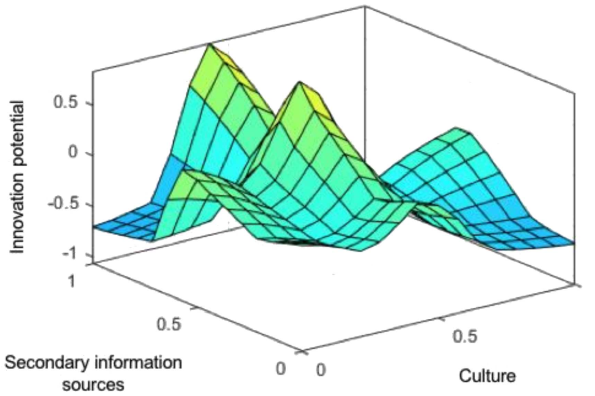

Fig. 8. The surface of the relationships between secondary information sources, culture and innovation potential.

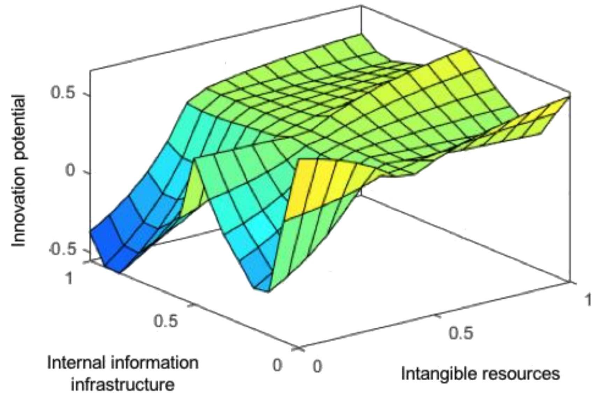

Fig. 9. The surface of the relationships between internal information infrastructure, intangible resources and innovation potential.

Table 5
The analyzed two cases and the resulted value of their sustainable innovation potential.

Variables	Case 1 values	Case 2 values
Motivation	0.927111	0.3
Strategy	1	0.6
Culture	0.451937	0.4
Technology modernity	0.802602	0.6
Stakeholder cooperation	0.391188	0.5
Seconder information sources	0.383006	0.8
External cooperation	1	0
Objective results	0.22918	0.1
Subjective results	0	0.5
Intangible resources	0.6	0.5
Internal information infrastructure	0.8	0.7
External information infrastructure	0.8	0.8
Age of experts	0.8	0.9
Push technologies	0.2	0.2
Pull technologies	0.781396	0.8
Material resources	0.371427	0.3
Sustainable innovation potential	**2**	**4**

The result of the first case from FIS turned out $= 0.4292$ using the conversation formula, it means IP $= 2$.

The result of the second case from FIS turned out $= 0.8599$ using the conversation formula, it means IP $= 4$.

These results – as expected based on the theoretical background – are equal the values presented in the above tables last row.

Conclusions

Having the results from the running model we draw up our conclusions in two fields: on methodology and on sustainable innovation potential.

The innovation intelligence decision-making problem is a very complicated task which structure is unknown (or the exploration would be very difficult) we can only deduce the structure based on *a priori* experience. However, because of the complexity, this can only be solved with a great computing background. We used a neuro-fuzzy solution to solve the problem which proved to be resulted in a very good solution. The assembled system has quickly and precisely gives results on appropriate accuracy. The results we are getting during the runs (two of them is shown in this paper) in most cases are equal with the expected values. Of course, if we were to expand the data that we can do based on experience, we can even fine-tune the system to a certain level. Overall the produced FISs are well approaching the problem-solving and our method as a decision-making method is suitable for solving the problem.

We showed in our research, that innovation potential can be efficiently approximated by our 16-variable fuzzy inference system.

Limitations

The main reason of the explosive spread of fuzzy systems in the nineties was the conviction that these methods can provide solutions to any kind of control problems and classical control systems will gave their place to these systems. It seems today that this conception was not correct mainly because of the limitations of the system. The most serious problem is that we do not have a generalized and systematic method for the efficient transformation of expert knowledge of experience into the rule base of a fuzzy inference system. Another big problem is that there is no such an algorithm, which would give the optimal number of fuzzy rules. It is not possible to measure the stability of the controlled system because the mathematical model is not known. It can also arise that the generated rules are not consistent for the human mind; there can be contradictions as well. The iteration of the model can be too long; fuzzification is time-consuming such as the complex operators of defuzzification.

Neural networks also have some weaknesses. The weights of the estimated networks are very difficult to interpret. The probability of finding not just a local minimum of error functions of the network during the long iteration process can be low when it does not converge towards the global minimum. The model requires a large size sample, which can significantly increase the hardware requirements of the system. It is also very time-consuming to reach the optimal architecture of the network and this process is often heuristic. The system might be overlearned which reduces the generalization ability of the model. In spite of these limitations the usage of these soft models worth the effort because the can reach much more effectiveness and have much less restrictive requirements than classical hard computing methods.

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