ANALYSIS OF SUSTAINABLE DEVELOPMENT USING FUZZY LOGIC PREDICTION MODELS AND ARTIFICAL NEURAL NETWORKS

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Abstract:
Sustainable development is a priority of policies in countries all over the world, regardless of their level of development; this is a dynamic and complex concept based on indicators with vague and difficult to measure characteristics such as resources, labor, education, infrastructure, the existence of modern equipment to ensure manufacturing performance and flexibility. A model of approach and analysis of sustainable development using these indicators with vague characteristics can be achieved by combining prediction models: artificial neural networks and fuzzy logic. Artificial neural networks are used in the study, as they have the advantage of working with hidden layers, and recursive backpropagation algorithms to predict the size of indicators for a certain period, while fuzzy logic is used for three-dimensional interpretation of interdependencies and trends of indicators. The model provides long-term, flexible management decisions by eliminating bottlenecks and assessing deviations from a target defined so that the final result ensures a fast and flexible solution through fast and durable reconfiguring.

Keywords: *neural networks, fuzzy logic, sustainable development, management, decision-making, sustainability*

JEL Classification: *A12, C63, D89*

1. Introduction

Rapid economic development and improved quality of life are achieved in close relation to sustainable development, but require an efficient management of natural and technological resources at all levels: global, regional, national or local. The constant emergence of new challenges and sustainable development indicators requires deciding on the priority of each problem. Because these indicators are characterized by uncertainty, a vague vision on new issues that arise, and mutual influences between indicators, it is preferable that they be analyzed using prediction models that bring forth hidden information that cannot be perceived through a classical analysis. The advantage of digital-linguistic dual analysis is the extensive area of research due to the linguistic variable. The paper addresses such a dual analysis using artificial neural networks (ANN) employed for forecasting and fuzzy logic employed for the three-dimensional interpretation of interdependencies between prediction data.

Different authors analyzed the use of artificial neural networks and fuzzy logic to evaluate sustainable development indicators, but the dualism of these analyses has not been addressed. Specific indicators, such as population density, GDP per capita, water, soil and air quality were analyzed to evaluate urban development (Daniela Hîncu, 2011; Marius Pislaru et all, 2011; Lucas Andrianos, 2015).

Energy resources, the risk of using pesticides and nitrates, air pollution, income and employment rate were used as indicators to analyze sustainable agriculture in Iran (Moslem Sami et all, 2013). Nenad Stojanović (2011) analyzed the tourism sector in natural reserves (protected areas) in terms of sustainable development by minimizing the impact of tourism on components such as economy, society, culture, and tourist satisfaction. For a qualitative

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analysis of sustainable development, Sung Hsueh-Lin (2013) used a combination of Delphi and fuzzy logic.

Sustainable development is also characterized by the use of flexible manufacturing systems and predictions can be achieved in interdependence with the professional development of the human factor by using artificial neural networks. A model of analysis of flexible manufacturing systems (FMS) was developed using Queueing networks (M. Jain et all, 2008). Petri type networks ensure appropriate modeling and analysis of complex FMS (Abdulziz M. El-Tamimi et all. 2011). An advanced research using a hybrid neuro-fuzzy system was carried out to analyze the sequence of operations performed by an operator in a FMS (Rajkiran Bramhane et all, 2014).

This research addresses the key objective of the National Sustainable Development Strategy - Romania 2013-2020-2030 (2008): "*Economic prosperity through the promotion of knowledge, innovation and competitiveness with an aim to ensure high living standards and full and high-quality employment*".

2. Indicators used in research analysis

The general structure of an FMS includes: machine tools, workstations, a transmission subsystem (automated guided vehicles - AGV), handling / processing systems (industrial robots), and a control system (a computer controlling the FMS). A FMS is operated by employees who are open to continuing education and training in order to manage resources at maximum capacity with minimized waste, and fewer system blockages so that resource productivity and the rate of growth of labor productivity ensure sustainable development.

Resource productivity, training, research and development spending, the growth rate of labor productivity per employee, the types of robots in use are representative indicators of sustainable development. There are other important indicators that contribute to the sustainable development of a nation, but our research aims to present a methodology of analysis and is based on the interpretation of a reduced set of data to highlight the practice of manipulating data to obtain valuable results; a very large number of indicators would have lead to confusion and an unclear methodology for readers that are less familiar with these concepts.

In this study we considered the following Indicators of Sustainable Development of Romania 2013, 2020, 2030 (http://www.insse.ro/cms/files/Web_IDD_BD_ro/index.htm):

1. **Objective 4. Sustainable consumption and manufacturing**

a) O4_1. Resource productivity;

b) O4_5. Waste generated by the main economic activities:
   - Mining industry;
   - Manufacturing industry;
   - Energy industry.

2. **Objective 9. Education and Training**

a) O9_5. The share of people based on their level of computer skills;

b) O9_6. The share of people based on their level of Internet skills;

3. **Objective 10. Scientific research and technological development, innovation**

a) O10_1. Total expenditure on research and development as a % of GDP

4. **Objective 11. Increase labor productivity and employment rate**

a) O11_1. The growth rate of labor productivity / employee;

The degree of industrial robotization of Romanian industry is added to the above-mentioned indicators, as presented in Figure 1.

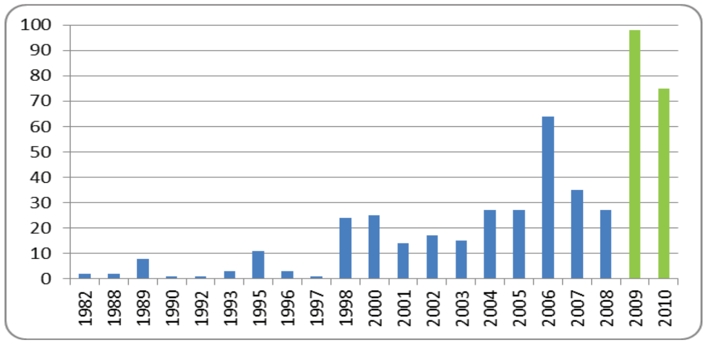

Figure 1 Industrial robots installed yearly in Romania between 1982-2010
Source: http://www.robotics-society.ro/noutati/2010%20IFR%20SRR.pdf

After the global economic crisis, Romanian companies focused on reducing the cost of goods, a target that could be achieved by increasing the number of machine tools with computer numerical control (CNC), which were developed based on NC machine tools (numerical control - NC), and the number of industrial robots (Industrial robots - IR) that evolved from those with fixed control algorithms to those with flexible control algorithms (including optical control). After 2008 there was a significant increase in the number of industrial robots in Romania, in line with the global upward trend (Figure 3).

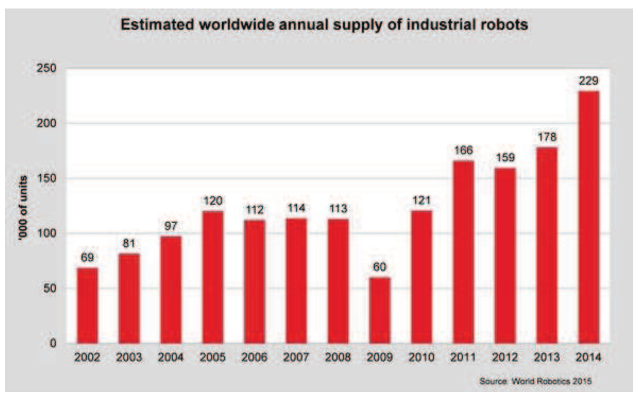

Figure 2 The dynamics of sales of industrial robots worldwide during 2002-2014
Source: http://www.ifr.org/industrial-robots/statistics/

Because the National Institute of Statistics does not publish current information about the industrial robots market in Romania, Figure 3 shows their distribution as of 31.12.2008.

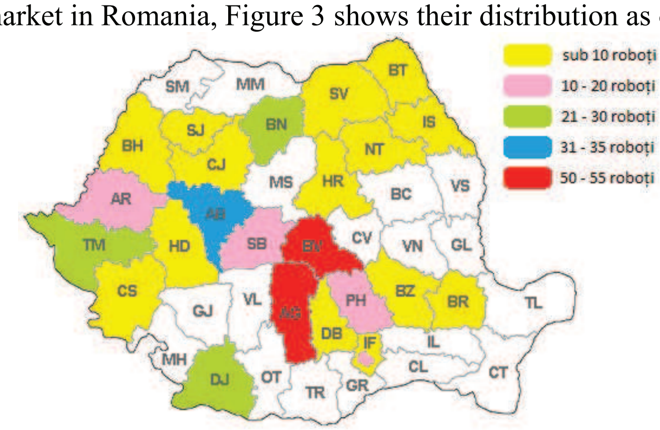

Figure 3 The territorial distribution of robots in Romania as of 31.12.2008
Source: processed by author based on data available at http://www.robotics-society.ro/noutati/SitRobotiRO2008.pdf

A mention-worthy aspect is the distribution of industrial robots for training in technical universities (students, graduates, doctoral students, teachers).

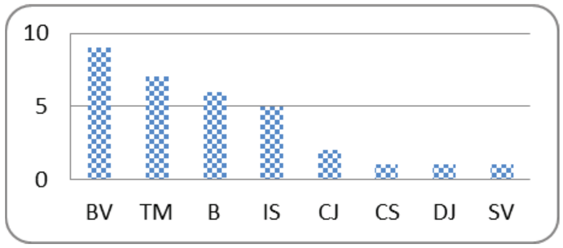

Figure 4. Distribution of industrial robots in technical universities in Romania as of 31.12.2008

Source: processed by author based on data available at http://www.robotics-society.ro/noutati/SitRobotiRO2008.pdf

3. Research methodology

3.1. Forecasting data with artificial neural networks – ANN

For the study, we used Visual Gene Developer[1] 1.7 - VGD (Build 762 - November 28, 2014, freeware), which was developed by the *Department of Chemical Engineering and Materials Science - University of California-Davis* and was based on a standard, backpropagation, learning algorithm.

Table 1 presents the input data[2].

Table 1 Input data

An	MP	Mining industry	Manufacturing industry	Energy Industry	PC skills	I skills	R&D %	Wp %	Robots
2006	0.87	199126793	9391852	102616494	2.43	1.96	0.45	7.3	64
2007	0.78	215065670	19397664	36478883	2.38	2.00	0.52	6.5	35
2008	0.66	140677024	11064033	7058116	2.43	1.96	0.57	8.4	27
2009	0.78	160193783	8089348	85751263	2.56	2.43	0.46	-5.2	98
2010	0.84	177441159	7320934	5887051	2.49	1.86	0.45	-0.5	75
2011	0.75	155694817	7497154	48866958	2.74	2.41	0.49	1.9	
2012	0.78				2.66	2.34	0.48	5.7	
2013					2.77	2.16	0.39	4.0	
2014					2.42	2.19		1.8	

Visual Gene Developer works with series of numbers in the [-1, 1] closed interval, which must therefore be demultiplicated in order to obtain sub-unit series (eg.: 93,911,852 must be demultiplicated by 100,000,000 to obtain 0.093911852).

Table 2 Demultiplicated input data

Zile	An	MP	Mining industry	Manufacturing industry	Energy Industry	PC skills	I skills	R&D %	Wp %	Robots
0.0365	2006	0.87	0.199126793	0.0939185	0.1026165	0.010	0.024	0.45	0.73	0.64
0.0730	2007	0.78	0.215065670	0.1939766	0.0364789	0.004	0.024	0.52	0.65	0.35
0.1096	2008	0.66	0.140677024	0.1106403	0.0070581	0.001	0.024	0.57	0.84	0.27
0.1461	2009	0.78	0.160193783	0.0808935	0.0857513	0.009	0.026	0.46	-0.52	0.98
0.1826	2010	0.84	0.177441159	0.0732093	0.0058871	0.001	0.025	0.45	-0.05	0.75
0.2191	2011	0.75	0.155694817	0.7497154	0.0488670	0.005	0.027	0.49	0.19	
0.2557	2012	0.78				0.005	0.027	0.48	0.57	
0.2922	2013					0.005	0.028	0.39	0.40	
0.3287	2014					0.005	0.024		0.18	
0.5479	**2020**									
0.9131	**2030**									

[1] http://visualgenedeveloper.net/index.html

[2] http://www.insse.ro/cms/files/Web_IDD_BD_ro/index.htm

Predictions for missing values and for 2020 and 2030 were made for the following configurations of neural networks:

Table 3 ANN configuration for predicting values

Parameter	Value		
	1st	2nd	3nd
Number of input variables	5	3	1
Number of output variables	4	6	9
Number of hidden layer	3	3	5
Node# of 1st hidden layer	7	6	10
Node# of 2nd hidden layer	9	9	10
Node# of 3nd hidden layer	6	6	10
Node# of 4th hidden layer	---	---	10
Node# of 5th t hidden layer	---	---	10
Learning rate	0,001	0,001	0,002
Momentan coefficient	0,1	0,1	0,1
Transfer function	Hyperbolic tangent		
Maximum # of training cycle	20000	20000	100000
Target Error	0,00001		
Initialization method of threshold	Random		
Initialization method of weight factor	No change		
Analysis update interval (cycles)	500		
Sum of error	0.0885759205	0,1302965581	0,0433704108
Avg error per output per dataset	0.0044287979	0,0031022990	0,0005354372
Processing time (sec)	23 sec	23 sec	2 min 24 sec

In Figure 5, the red line corresponds to big *positive* numbers (which tend to +1) and the purple line to big *negative* numbers (which tend to -1). Most of the flow of information is centered on green and blue, around ± 0. The width of the line is proportional to the weight factor in absolute value or the threshold value.

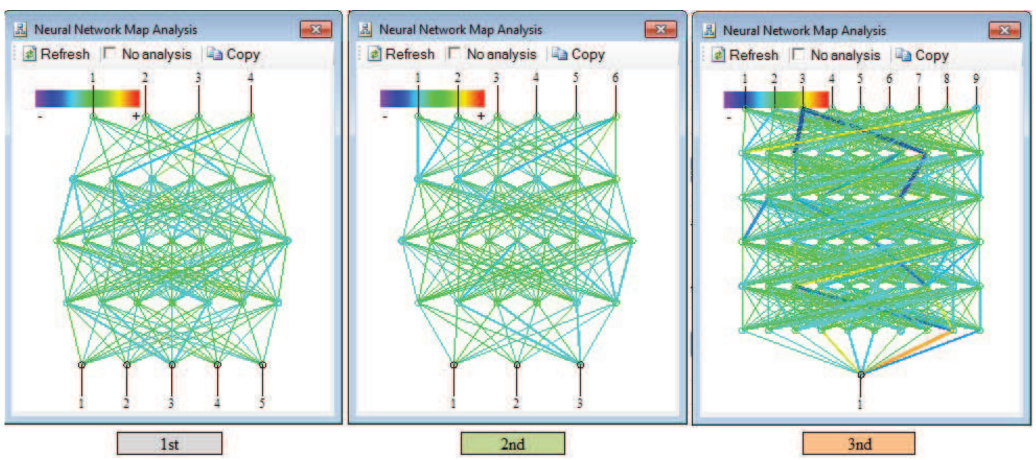

Figure 5 Information flow through ANN for the three prediction cases

Table 4 Prediction values

Zile	An	MP	Mining industry	Manufacturing industry	Energy Industry	PC skills	I skills	R&D %	Wp %	Robots
0.0365	2006	0.87	199126793	9391852	102616494	2.43	1.96	0.45	7.3	64
0.0730	2007	0.78	215065670	19397664	36478883	2.38	2.00	0.52	6.5	35
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0.1461	2009	0.78	160193783	8089348	85751263	2.56	2.43	0.46	-5.2	98
0.1826	2010	0.84	177441159	7320934	5887051	2.49	1.86	0.45	-0.5	75
0.2191	2011	0.75	155694817	7497154	48866958	2.74	2.41	0.49	1.9	70
0.2557	2012	0.78	169455500	14343620	51826930	2.66	2.34	0.48	5.7	49
0.2922	2013	0.78	173995400	13230110	46433510	2.77	2.16	0.39	4.0	59
0.3287	2014	0.79	167036100	12478700	46339510	2.42	2.19	0.48	1.8	71
0.5479	2020	0.77	138847300	9042317	83401710	2.60	3.70	0.48	-0.58	92
0.9131	2030	0.76	142992100	8833937	122321500	2.50	4.30	0.49	-0.64	93

3.2. Analysis of prediction data with fuzzy logic

Step 1. Define **input variables.**

Table 5. Defining input variables and symbols

Symbol	Name	UM
MP	Resource productivity	[thousand LEI in prices 2005/ton]
Mi.I	Mining industry	[tons]
Ma.I	Manufacturing industry	[tons]
EI	Energy Industry	[tons]
PCS	Individuals' level of computer skills	[%]
IS	Individuals' level of Internet skills	[%]
R&D	R&D expenditure as GDP percentage	[%]
Wp	Growth rate of labour productivity per employed person	[%]
R	Robots	[pieces]

Step 2. Divide each of the 8 input factors (quantitative variable) on **intervals** based on which we will be build each fuzzy number. To ensure a rigorous analysis, PC skills and I skills data sets will be used as a ratio of I/PC skills.

Table 6. Prediction data

An	MP	Mining industry	Manufacturing industry	Energy Industry	I / PC skills	R&D %	Wp %	Robots
2006	0.87	0.199126793	0.0939185	0.1026165	0.81	0.45	0.73	0.64
2007	0.78	0.215065670	0.1939766	0.0364789	0.84	0.52	0.65	0.35
2008	0.66	0.140677024	0.1106403	0.0070581	0.81	0.57	0.84	0.27
2009	0.78	0.160193783	0.0808935	0.0857513	0.95	0.46	-0.52	0.98
2010	0.84	0.177441159	0.0732093	0.0058871	0.75	0.45	-0.05	0.75
2011	0.75	0.155694817	0.7497154	0.0488670	0.88	0.49	0.19	0.70
2012	0.78	0.169455500	0.1434362	0.0518269	0.88	0.48	0.57	0.49
2013	0.78	0.173995400	0.1323011	0.0464335	0.78	0.39	0.40	0.59
2014	0.79	0.167036100	0.1247870	0.0463395	0.90	0.48	0.18	0.71
2020	0.77	0.138847300	0.0904232	0.0834017	1.42	0.48	-0.58	0.92
2030	0.76	0.142992100	0.0883394	0.1223215	1.72	0.49	-0.64	0.93

Table 7. Define interval limits and build fuzzy numbers

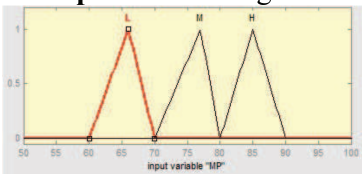
	Set Range	Fuzzy Range	Merbership function	Range 1	Range 2	Range 3	Range 4	Range 5
MP	[0.66 – 0.87]	[50 100]	trimf		[60 66 70]	[70 77 80]	[80 85 90]	
Mi.I	[0,1388 – 0.2150]	[13 22]	trimf	[13 14.08 15.41]	[15.41 16.1 16.93]	[16.93 17.57 18.46]	[18.46 19.91 19.98]	[19.98 21.5 22]
Ma.I	[0.0732 – 0.1939]	[0 20]	trimf		[4 7.41 8]	[8 9.28 12]	[12 13.35 16]	[16 19.39 20]
EI	[0.0058 – 0.1223]	[0 13]	trimf	[0 0.65 2.6]	[2.6 4.6 5.2]		[7.8 9.1 10.6]	[10.6 12.23 13]
I/PC_S	[0.74 - 1.72]	[0 2]	trimf		[0.4 0.76 0.8]	[0.8 0.87 1.2]	[1.2 1.42 1.6]	[1.6 1.72 2]
R&D	[0.39 – 0.57]	[0 100]	trimf		[20 39 40]	[40 49 60]		
Wp	[-5.2 – 8.45]	[-6 9]	trimf	[-6 -5.2 -3]	[-3 -0.58 0]	[0 1.8 3]	[3 4.9 6]	[6 7.4 9]
R	[27 – 98]	[0 100]	trimf		[20 31 40]	[40 54 60]	[60 70 80]	[80 94 100]

Step 3. Set the size of the **linguistic variable** for input variables.

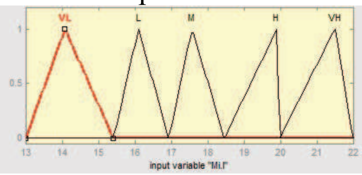
Table 8. Set the size of the linguistic variable for input variables

	Set Range	Fuzzy Range	Merbership function	VL	L	M	H	VH
MP	[0.66 – 0.87]	[50 100]	trimf		L	M	H	
Mi.I	[0,1388 – 0.2150]	[13 22]	trimf	VL	L	M	H	VH
Ma.I	[0.0732 – 0.1939]	[0 20]	trimf		L	M	H	VH
EI	[0.0058 – 0.1223]	[0 13]	trimf	VL	L		H	VH
I/PC_S	[0.74 - 1.72]	[0 2]	trimf		L	M	H	VH
R&D	[0.39 – 0.57]	[0 100]	trimf		L	M		
Wp	[-5.2 – 8.45]	[-6 9]	trimf	VL	L	M	H	VH
R	[27 – 98]	[0 100]	trimf		L	M	H	VH

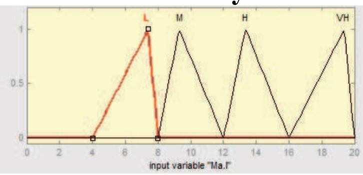
Step 4. Build triangular functions for input variables in **Matlab R2011b - fuzzy menu**.



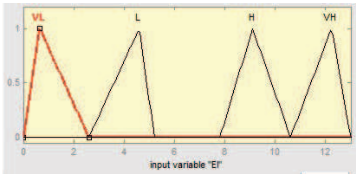
a) fuzzy trimf function for MP



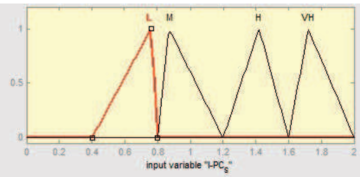
b) fuzzy trimf function for Mi.I



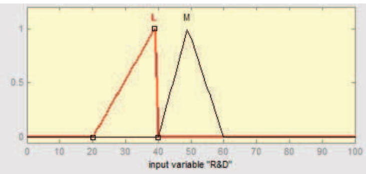
c) fuzzy trimf function for Ma.I



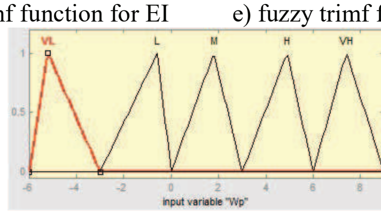
d) fuzzy trimf function for EI



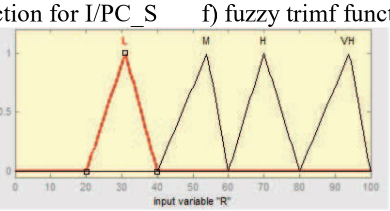
e) fuzzy trimf function for I/PC_S



f) fuzzy trimf function for R&D



g) fuzzy trimf function for Wp



h) fuzzy trimf function for R

Figure 6. Built functions for input variables in Matlab R2011b

Step 5. Set **the prediction interval**, the interval limits and the center of the interval for the output variables.

Table 9. Define intervals and linguistic output variables

	Fuzzy Range	Merbership function	Range 1	Range 2	Range 3	Range 4	Range 4
OUTPUT	[0 -100]	trimf	[0 11 22]	[18 30 42]	[38 50 62]	[58 70 82]	[78 89 100]
			VL	L	M	H	VH

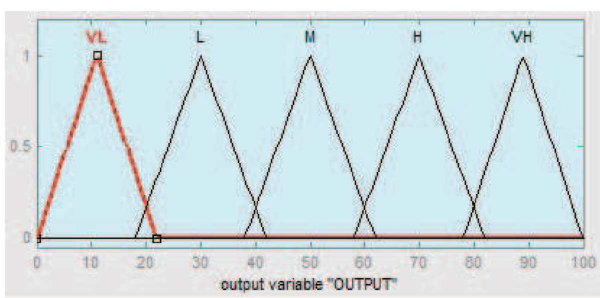


Figure 7. Build functions for the output variable in Matlab R2011b

Step 6. Define **rule set**. Input variables are placed under the incidence of the IF condition, while output variables are placed under the incidence of the THEN conclusion. Two researchers will set different rules, depending on the practical experience of each of them, the interpretation of linguistic variables, the degree of atomization (grain) of rules, the way that membership functions are set, etc.

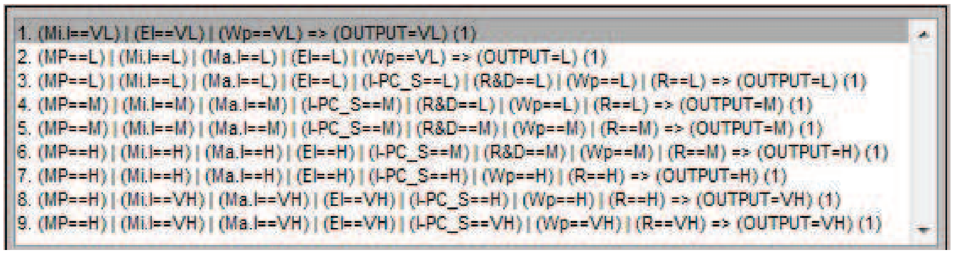


Figure 8. Define rule set

In cases of multiple input/ output variables, the researcher can choose logic combinational connectors like OR (OR) or AND (AND). It's also possible to select the NOT logic connector of negation for input/ output variables.

If a rule has a higher weight than the other rules in the process of inference, the value of the weight will be specified in the **Weight** box. The weight is displayed in brackets to the right of each rule.

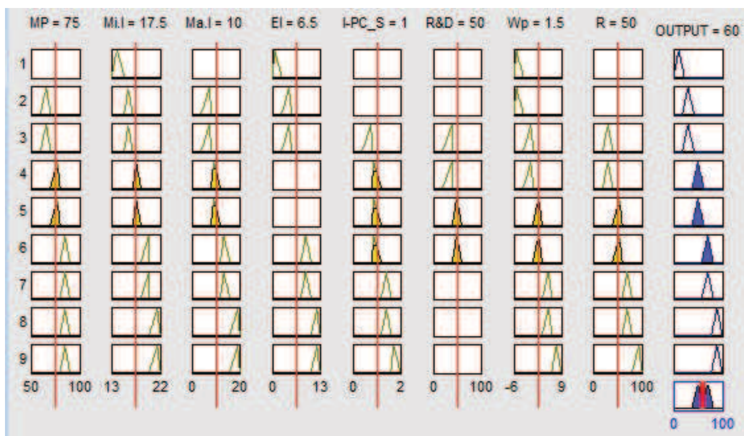


Figure 9. Graphical representation of the result of executing the rules

Step 7. Run the application and interpret data

A. Waveform Analysis

For a correct interpretation of output data we must analyze the waveforms of input variables.

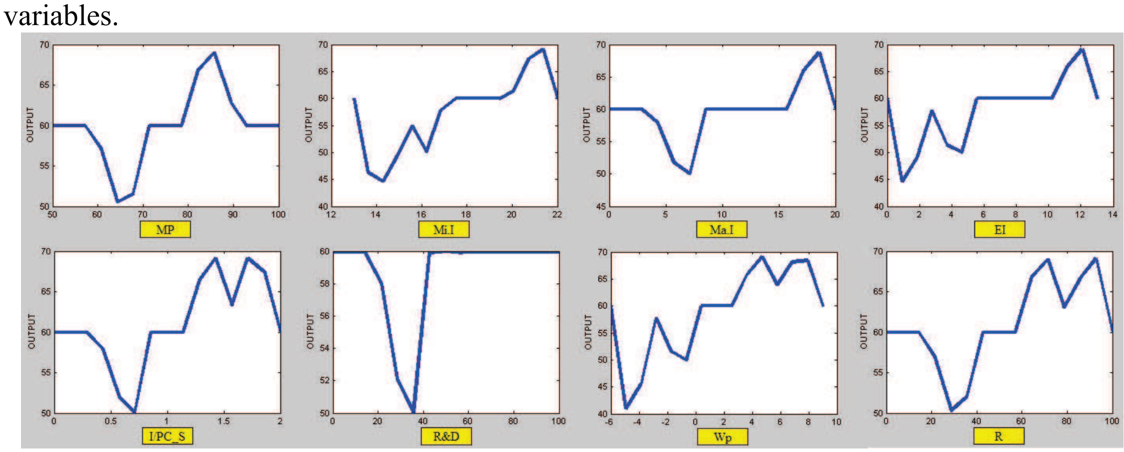


Figure 10. Waveforms of input variables

Figure 10 shows that the input variables have a diversified ripple in terms of waveform.

The following models characterize waveforms:

↳ U – growth–stagnation–decline - shows a lack of force to rejoin the growth trend and lower economic growth – economic depression;

↳ L – decreasing–stagnation – a situation that is not recommended;

↳ V – force during early recovery, with a potential risk to transform into W. The sharper the tip, the faster the recovery. Figure 10 shows that most waveforms are characterized by a broken V - 5 cases;

↳ W and M – mirror models – both are characterized by collapse after a period of increase.

The interpretation of letters is done in *the opposite direction* for the *Mi.I, Ma.I and EI* indicators, as they represent the *levels of waste produced by the respective industry*.

B. Area analysis and quiver direction

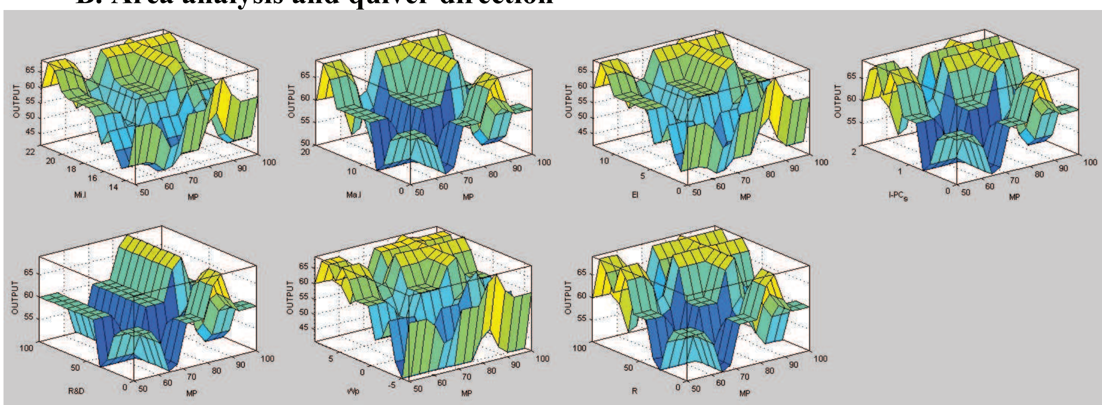


Figure 11. Shape of Mi.I, Ma.I, EI, I/PC_S, R&D, Wp and R areas in relation to MP

Resource productivity quickly affects mining and energy industry waste through rapid growth in the first part of the interval. Manufacturing industry is difficult to influence, as it needs more time to follow the same trend.

Similar shapes of areas are seen for the I/ PC skills ratio, the growth rate of labor productivity per employee and the number of industrial robots that have the same evolution in relation to resource productivity.

There is a particular area for resource productivity in relation to research and development that shows that research and development activities increase only if resource productivity is high.

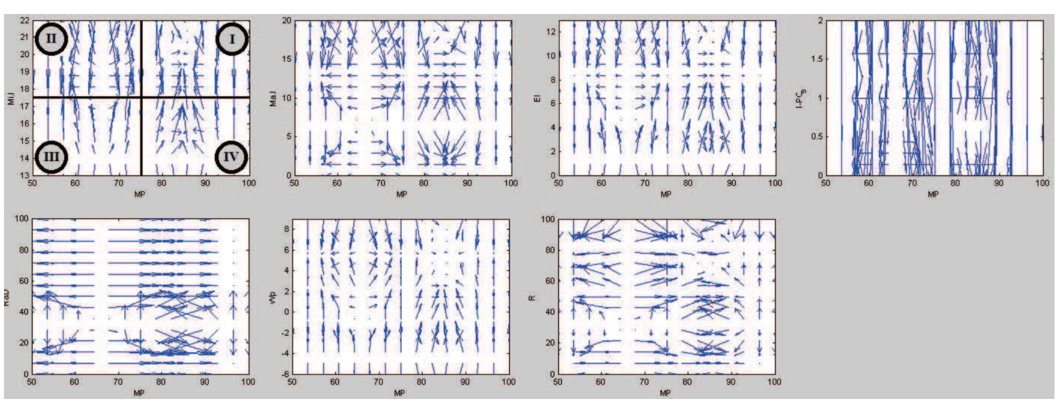


Figure 12 Trends of action of the Mi.I, Ma.I, EI, I/PC_S, R&D, Wp and R quivers in relation to MP

Trends of action of quivers for industries (mining, manufacturing and energy), the rate of growth of employee productivity and the number of industrial robots are similar in all four quadrants (Figure 12):

↳ I^st quadrant with a trend from the edges to the center – superior results;

↳ II^nd quadrant with a trend from the center to the edges – average results;

↳ III^rd quadrant with a trend from the edges to the center – inferior results;

↳ IV^th quadrant with a trend from the edges to I^st quadrant – average results.

Depending on the degree of productivity of resources, the I/ PC_skills ratio aligns vertically with a dominant trend toward the middle of quadrants I and IV and a recessive trend toward the edge of quadrants II and III, regardless of the skill level of the I/ PC_skills ratio.

Research and development aligns horizontally with a dominant trend toward quadrants I and IV if resource productivity is over 65%.

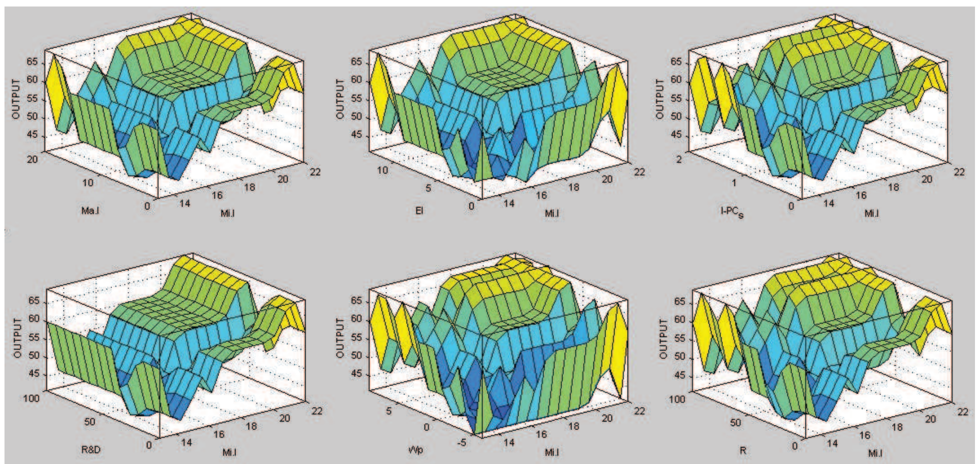


Figure 13. The shape of the Ma.I, EI, I/PC_S, R&D, Wp and R areas in relation to Mi.I

If Ma.I, EI, I/PC_S, R&D, Wp and R areas are analyzed in relation to Mi.I (Figure 13) we notice that, except for the R&D indicator, areas have approximately the same shape, although it must be noted that for the first part of the Mi.I interval, [13 16] respectively, where certain mutual influences occur, they have a W shaped evolution. In this case, R&D activity increases only if mining industry productivity is significant and thus maintains resource productivity.

The trend of the Ma.I, EI and Wp quivers (Figure 14) is approximately identical in all 4 quadrants, with a concentration toward the center of the I^st quadrant corresponding to a high increase development. For R&D and industrial robots there is a horizontal alignment to several levels depending on the funding allocated to these areas. The industrial robots indicator has a clear definition on 4 levels. The R&D indicator is characterized by:

- 2 clear levels for low and medium levels of allocation of financial resources;
- 8 poorly defined levels, out of which 6 are for elevated levels of allocation of financial resources;

The I/PC_S indicator has chaotic trends marked by clusters of concentration:

✓ from the edges to the middle in quadrants I and IV;

✓ from the middle to the edges in quadrants II and III;

which show the disorientation of mining sector employees regarding professional development.

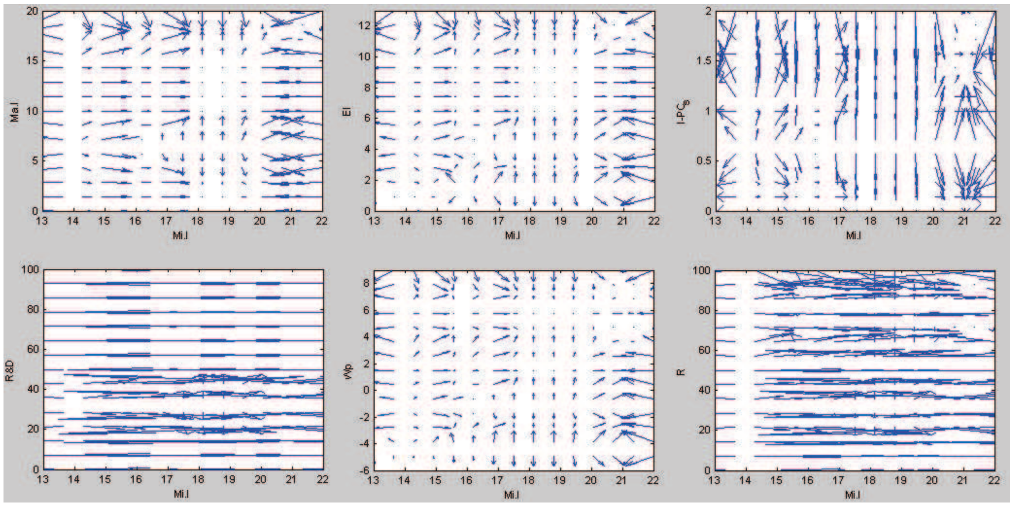


Figure 14. Trends of action of the MP, Ma.I, EI, I/PC_S, R&D, Wp and R quivers in relation to Mi.I

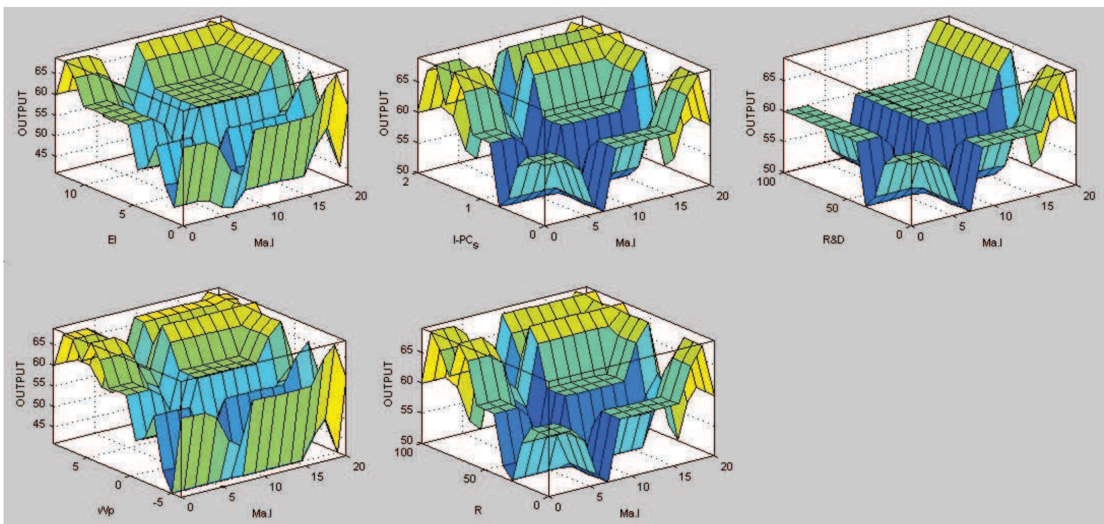


Figure 15. The shape of the EI, I/PC_S, R&D, Wp and R areas in relation to Ma.I

EI, I/PC_S, R&D, Wp and R areas in relation to Ma.I are nearly identical to areas in relation to MP resource productivity, the difference being the change of level of the Ma.I indicator from 18 to 19 (Figure 15).

Evident changes of the trend of the quiver direction (Figure 16) are noted for waste produced by the energy industry and the growth rate of labor productivity per employee from high to low concentration. The trend of direction of the R&D and industrial robots indicators quivers in relation to Ma.I is identical to that in relation to MP.

For the I/ PC_S indicator we note a movement toward the right edge of quadrants I and IV (significant waste from manufacturing industry) regardless of the skill level of employees.

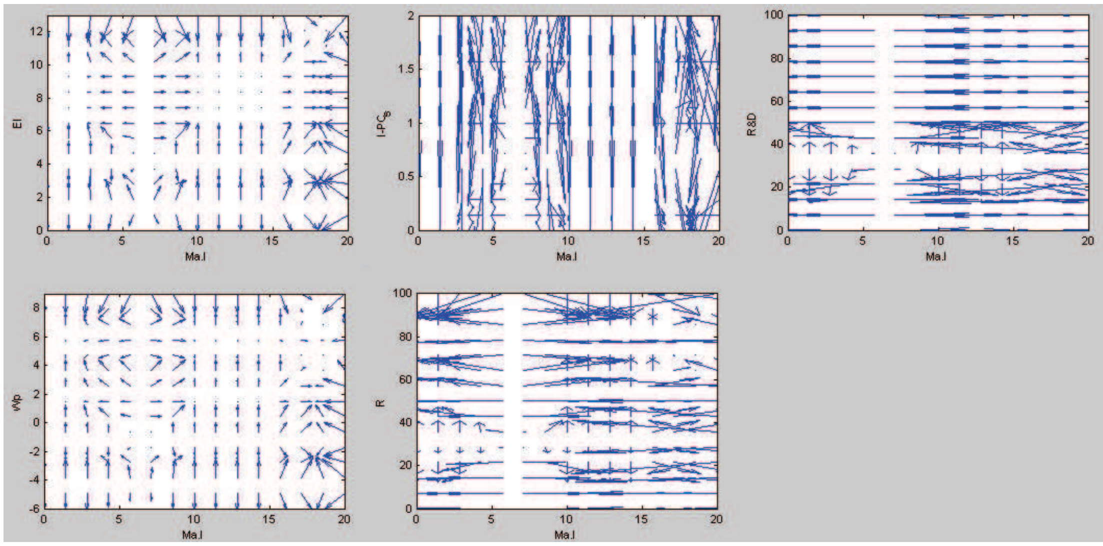


Figure 16. Trends of action of the EI, I/PC_S, R&D, Wp and R quivers in relation to Ma.I

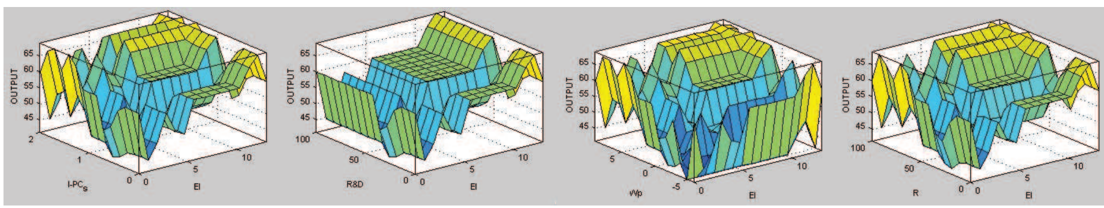


Figure 17. The shape of the I/PC_S, R&D, Wp and R areas in relation to EI.

In this case, the I/ PC_S, R&D, Wp and R areas in relation to EI (Figure 17) are almost identical depending on Mi.I resource productivity, while the difference is explained by the gaps between the coordinates of initialization of the graph, as reinforced by the trends of action of quivers shown in Figure 18.

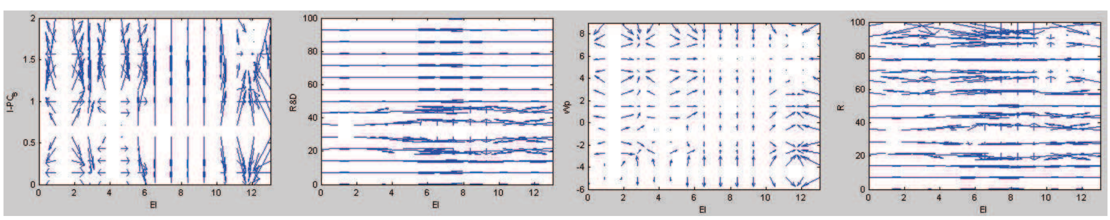


Figure 18. Trends of action of the I/PC_S, R&D, Wp and R quivers in relation to EI.

The I/ PC_S ratio in the [1.5 to 2] interval has an important role in the evolution of R&D, Wp and R in terms of the areas, as it changes their shape throughout the interval they represent.

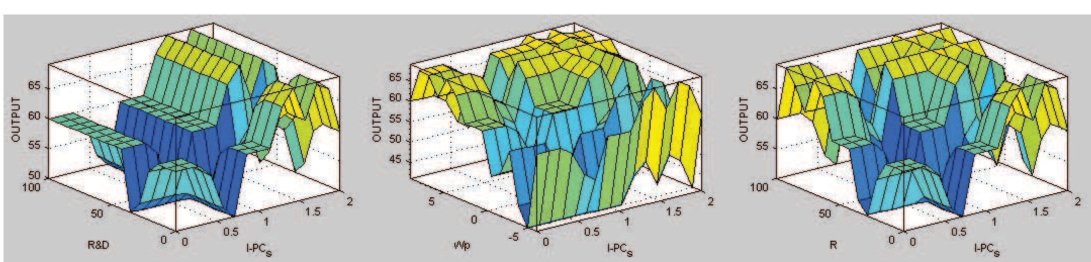


Figure 19. The shape of the R&D, Wp and R areas in relation to I/PC_S.

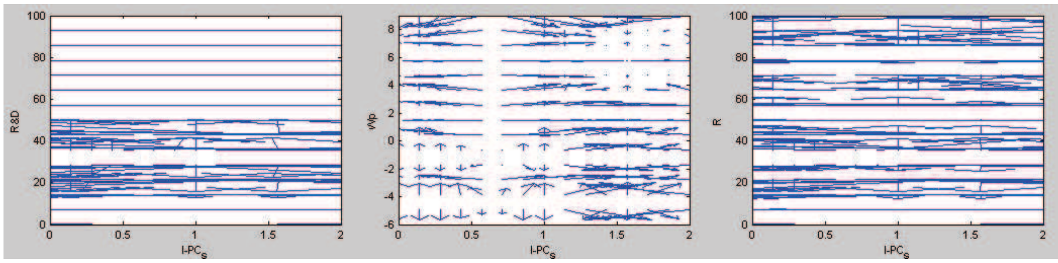


Figure 20. Trends of action of the R&D, Wp and R quivers in relation to I/PC_S.

Figure 20 shows that analyzing R&D in relation to I/ PC_S produces a high concentration of the I/ PC_S ratio in the [0 0.5] interval and an average concentration in the [1.5 2] interval, both having low and medium levels of financial resources for research and development. The rate of growth of labor productivity per employee has different trends in all 4 quadrants. All employees with different levels of the I/ PC_S ratio approach the use of IT represented by robots, while two diametrically opposed categories emerge:

- ❖ I/PC_S between [0 0.6] for levels of 20 and 40 robots;
- ❖ I/PC_S between [1 2] for levels of 70 and 90 robots,

the interest in professional development increasing along with the number of industrial robots.

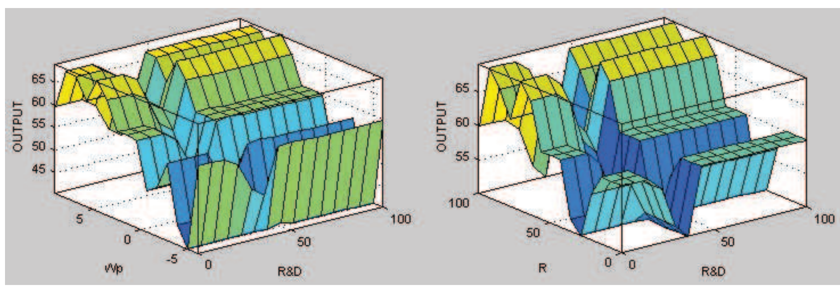


Figure 21. The shape of the Wp and R areas in relation to R&D.

Analyzing Figures 21 and 22, we can observe the targeted growth rate of labor productivity per employee, with an attempt to break this pattern when resources allocated to the R&D indicator lag around 30% for a positive productivity. For higher percentages, opposite trends of Wp begin to appear around the [0 5] interval. Two levels of industrial robots in relation to R&D can be observed:

1. 30-0 industrial robots with a downward trend, regardless of the amount allocated to R&D;
2. 80 industrial robots attracting R&D, regardless of the amount allocated in the [30-80] interval and downward trends for the [100-80] interval regardless of the amount allocated to R&D;

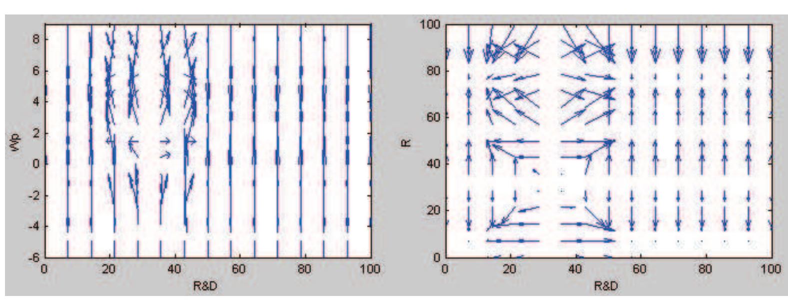


Figure 22. Trends of action of the Wp and R quivers in relation to R&D

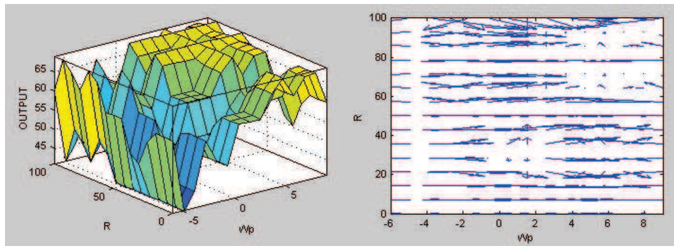


Figure 23. The shape of the area and trends of action of the R quiver in relation to Wp

A key element of this study is the impact of the number of industrial robots (R) and the growth rate of labor productivity per employee (Wp). A number of robots between 20-40 (Figure 23) generate a 4-6% increase of Wp, with a trend towards 8%. An increase in the number of robots to 80-100 leads to a Wp rate of around 2%, explained by the fact that there are no qualified people to handle such equipment since Romania restrains from professional development (see analysis in relation to Mi.I), contrary to the statements made above for Figure 20.

3. Conclusions

It can be concluded that entrepreneurs in Romania are reluctant to make new investments in equipment type industrial robots and CNC machines, due to high investment recovery cycle coupled with some uncertainty orders and economic fluctuations. In this context, no framework and conditions for the sustainable development of Romania are created.

Also, only a small number of industrial robots are available to technical universities, which influences the training of specialists who choose to practice their profession only in counties where there are at least 10-20 industrial robots.

Table 10 Final result using ANN and fuzzy logic

An	MP	Mining industry	Manufacturing industry	Energy Industry	I / PC skills	R&D %	Wp %	Robots	Result
2006	H	H	M	H	M	M	M	H	M-H
2007	M	VH	VH	L	M	M	M	L	M-H
2008	L	VL	M	VL	M	M	M	L	L
2009	M	L	L	H	M	M	L	VH	M
2010	H	M	L	VL	L	M	L	H	L-M
2011	M	L	L	L	M	M	M	H	L-M
2012	M	M	H	L	M	M	M	M	M
2013	M	M	H	L	L	L	M	M	L-M
2014	M	L	H	L	M	M	M	H	M
2020	M	VL	M	H	H	M	L	VH	M
2030	M	VL	M	VH	VH	M	VL	VH	M-H

Romania will maintain the current trend of economic development with a focus on sustainable development, having small positive or negative deviations from this average trajectory that will reoccur in a short time span of 1-2 years.

The analysis of Multi-Input-Multi type-Output (MIMO) data sets using neural networks and fuzzy logic and comparative analyses using different software for the same data set are the subject of further research.

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