Assessing key stakeholder perceptions to build a strategy for biorefineries deployment in rural areas

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Summary

Agroenergy, a relatively simple and mature technology to convert biomass into heat and electric energy, may represent a good opportunity to introduce the biorefinery schemes in rural areas. However, to guarantee the feasibility of new investments in this innovative sector, the commitment of all relevant players, and the sharing of their embedded knowledge of local conditions will play a crucial role. In this paper, we propose a modified neural network model to analyse the knowledge extracted from different groups of actors, in order to prevent the definition of strategic plans which may not be not fully consistent. We propose a methodology to support the strategic planning of the agroenergy innovation deployment in rural areas, based on the logical framework of the SWOT analysis, through which the most relevant factors affecting the expectations of local informed actors are identified. Subsequently, a modified multilayered feed-forward neural network is proposed to analyse the qualitative data, in order to verify their consistency. The results obtained from a case study in the province of Foggia (Italy) show that the level of consistency between the perceived factors affecting the deployment of the technology and the expectations towards the successful adoption of agroenergy at local level may vary depending on the degree of involvement and commitment of local players. This may represent a relevant issue for the definition of long-term strategic planning.

Keywords: embedded knowledge; multilayered feed-forward neural networks; SWOT analysis; agroenergy; strategic planning

JEL Classification codes: D83; O32; Q42

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1. Introduction

As the main source of organic carbon is largely produced by the agricultural sector, the European Union considers the development of biorefinery in rural areas as an effective strategy to foster the low carbon development path, (European Commission, 2012). Agroenergy, a relatively simple and mature technology to convert biomass into heat and electric energy, may represent a good opportunity to revitalize the economy in rural areas, where there is a lack of investments, leading to a high risk of depopulation and desertification.

Despite these benefits, several barriers hinder the development of agroenergy in rural areas, such as the lack of the main factors needed to promote technological investments (e.g. financial capital, professional skills, infrastructures, etc.), and the large diversity in the nature of biomass, which is closely related with the agricultural activities of each region.

Due to the low economic value of the biomass, it is important to minimize the incidence of transportation and transaction costs, without which the project will not be economically feasible, nor sustainable over time.

For this reason, to guarantee the feasibility of new investments in this sector, the designing of specific tailored projects of investment, based on a strong commitment of all relevant players, and site-specific innovative solutions involving embedded and (often) implicit knowledge plays a crucial role. This approach, in its turn, requires a process of convergence of the expectations of the main stakeholders around small scale plants, which are fed with locally available biomass.

Unfortunately, the early stage of development of an innovation is characterized by a lack of information regarding the possible evolution in terms of economic resources, market perspectives, institutional changes, etc. In order to provide at least the description of the context, a traditional SWOT analysis is often adopted, providing a general overview of the relevant aspects which may affect the development and the success of the innovation. Distinction is made between the factors which can be controlled by the actors directly involved in the project (i.e. strengths and weaknesses) and factors which cannot be controlled and describe the general context (i.e. opportunities and threats).

In the case of agroenergy projects, since the biomass is mainly available in rural areas, the involvement and commitment of local stakeholders is crucial, for the success of the initiative. Therefore, in order to favourite the convergence of expectations of actors involved in the innovation, we conducted a SWOT analysis aimed at extracting knowledge which is embedded into the local actors.

In this paper, we propose a modified neural network model to analyse the knowledge extracted from different groups of actors, in order to prevent the definition of strategic plans which are not fully consistent. In practice, we propose a methodology able to verify the consistency of the relationship existing between SWOT factors and the level of expectations formulated by a group of informed actors.

We present the case study of Foggia province, where a first "critical mass" has been created around a "research capacity" 7th EU-REGOPOT project financed by the EU, aiming at the creation of an agroenergy research facility centre and the formation of an integrated stakeholders' platform, to foster the innovation in this sector.

2. THEORETICAL FRAMEWORK

Although rural areas are well endowed with feedstock for energy purposes (i.e. biomass), we cannot expect a spontaneous formation of this sector within theme. This is due to the existence of some unfavorable conditions, more linked to the socio-economic domain than to the material resources. Some examples are the diffuse resistance to adopt innovation, difficulty to cooperate, absence of a clear market. In order to overcome these shortcomings a stable coordination among the various actors (e.g. farmers, food processors, policy makers, investors, final users, stockholders and local community) is needed.

Such a coordination cannot arise without the sharing of a common vision capable of attracting scarce resources into the new investment (Lopolito et al. 2015, Bijlsma et al., 2011). The formation of a guiding vision is a process referred in literature as convergence of expectations (Kemp et al., 2001). It contextualises and defines the new business, explaining its strengths with the aim to spread it among the stakeholders and to be accepted by a critical mass of innovation actors. This process represents the first step toward the formation of an innovation niche (Geels, 2004), stressing the fact that the actors decide whether being involved or not to risky projects on the basis of their expectations (Van der Laak et al., 2007). The convergence around a shared vision is essential in overcoming initial barriers as diverging interests and mistrust. Van Lente (1993) proposes a theoretical cycle, framing the process of formation and convergence of actors' expectations.

A fundamental part of this model is represented by the external conditions, with respect to the innovation niche, produced at the so-called *regime* or *landscape* level or in other protected spaces (as cultural process, resources reduction, or regulation change, R&D breakdown), that generate opportunities for developing new technology. The second step is the translation of these opportunities in promises related to the use of the new technology. The literature use the term promises to stress the fact that the new technology lacks clear market and functionality but presents interesting future development. When the promises embedded in the vision reach a wide level of sharing, they become constructive forces capable of enrolling key actors and their resources for specific roles, defining which are the strategic actions that should be included in the agenda and which should be kept off. The agenda is then decoded into tasks, specifications and requirements (Geels and Raven, 2006). This process results in a strategy based on the activities, the requirements, and the experimentations that are carried out in the niche. Tacit and embedded knowledge is mobilized and shared in this phase. As a consequence, the experimentations and the activities change dynamically the expectations, and therefore the cycle is closed. At the end, not only the external circumstances, but also the internal niche dynamic influence the original vision that can be confirmed (when the results match the expectations) or change it.

Here we stress that, as emerged from this discussion, a central element of the process of convergence is represented by the development of a common understanding of the facts around the novelty and the sharing of tacit and embedded knowledge. This is the main the core of the process we aim at investigate. In the following section, a rational and reproducible method to breaking down this process is presented.

3. METHODOLOGY

3.1. Artificial Neural Networks to extract embedded knowledge

In this paper we adopt a typical participatory approach, where the strategy is framed by the people directly involved by the project, according to a participatory, transparent and democratic method. In particular, we adopted a semi-qualitative method inspired to the SWOT analysis, where the expectations of participants towards the success of an initiative or project depend on the combination of internal (with respect to the acting group) factors, namely Strengths and Weaknesses, and external factors, that is Opportunities and Threats. The SWOT analysis, being a well established qualitative method to support innovative projects at early stages, is also suitable to framing the interactive dialogue among different stakeholders. Therefore, by combining the basic advantage of SWOT analysis with participatory approaches we aim at the achievement of an action learning with collective learning occurring during a planned series of meeting with several supporting groups.

In our case of study, three groups of people participated to a mail survey to identify the most relevant SWOT factors affecting the development of agroenergy innovation system in rural areas. The data collected at this stage, have been analysed through a specific type of artificial neural network, capable of simulating the relevance of each factor identified by the participants, and trying to assess the influence exerting on their expectations.

In particular, we developed a specific type of multilayer artificial network (White et al., 1992) to disentangle the complex perception of different groups of stakeholders and opinion makers towards the possible development scenario of agroenergy projects in the province of Foggia (Southern of Italy).

From the technical point of view, the neural network is able to:

- perform the weights estimation, that is, the strength of the relationship existing between two variables;

- analyse the intra-networks relations, to identifying strong and weak relations among the variables of the model;

- compare the relations between different groups, in order to understand their knowledge structure.

In this paper, we will create a neural network capable of learning the collective perception of SWOT variables, with regard to the expectations of the initiative. A comparison between three different groups of participants will be made based on the assessment of the consistency of each SWOT factor with the degree of expectation. In other words, the network will be used to a) replicate the collective knowledge of participants, and b) to verify whether S and O are positively correlated to the degree of expectation, while W and T are negatively correlated to the degree of expectation.

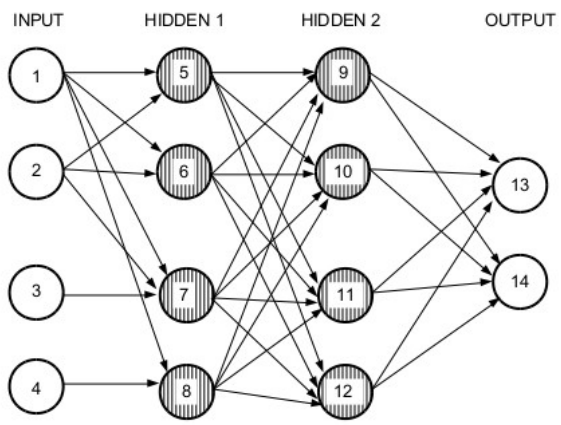
3.2. Design of the network architecture

The basic structure of the network refers to feed-forward multilayer neural network. Feed-forward networks are conceived to transmit an input signal throughout the subsequent units of the network, which finally contributes to the final value of output unit(s). This conceptual mechanism is coherent with the SWOT analysis, where each factor contributes to the formation of the expectations.

The presence of one or multiple (hidden) layers between the input and the output unit, provides the network the learning ability of the observed values, despite the presence of noise or redundancy. The presence of hidden layer(s) enables the network to approximate linear, non linear, or discontinuous functions which may be suitable to estimate the relationship between input and output variables (Beltratti et al., 1996).

A basic structure of this type of network is provided in Figure 1. Compared to classical networks reported in the literature, two types of input variables are differentiated. A first type, formed by input units which affect the whole network (units 1 and 2), emulate the role of S and W variables. A second type, is formed by inputs (units 3 and 4) which affect only part of the network, and emulate the role of O and T variables.

Figure 1: Conceptual structure of a multilayered feed-forward neural network



Source: adapted from Beltratti et al., 1996

These networks are usually calibrated by a supervised training, where internal values of the input units and strengths of links are calculated with learning algorithms (e.g. back-propagation of the error), based on a dataset of real observations containing either input and output values.

4. CASE STUDY

In year 2011 the EU Commission funded the University of Foggia with a 7th FP-REGPOT project aimed at promoting the scientific and technological advancement in research on agroenergy. Besides the academic and scientific relevance of the project, aimed at unlocking the potential of research and capacity of the university staff, the creation of a core facility and the formation of a multidisciplinary group was foreseen

as a strategic initiative to foster the promotion of agroenergy in the Southern Europe and, in particular, in the Mediterranean.

In order to perform a preliminary evaluation exercise on the progress of the project in terms of capacity to achieve the expectations of the involved actors, a SWOT analysis was performed in 2014, to three groups of people, differently involved by the project.

4.1. The network structure

Considering the conceptual framework already described in the previous session, a modified version of feed-forward multilayer network has been created, considering the number of possible input and output variables. The network prototype was formed by 11 Input units – type 1, 12 Input units – type 2, 23 hidden units – layer 1, 23 hidden units – layer 2, 3 output units (Figure 2).

4.2. Training the network prototype for testing purposes

Is the network capable to correctly interpret the logical meaning existing between input and output variables, according to a SOWT analytical framework, starting from a consistent set of exhibited multiple agents' behaviour?

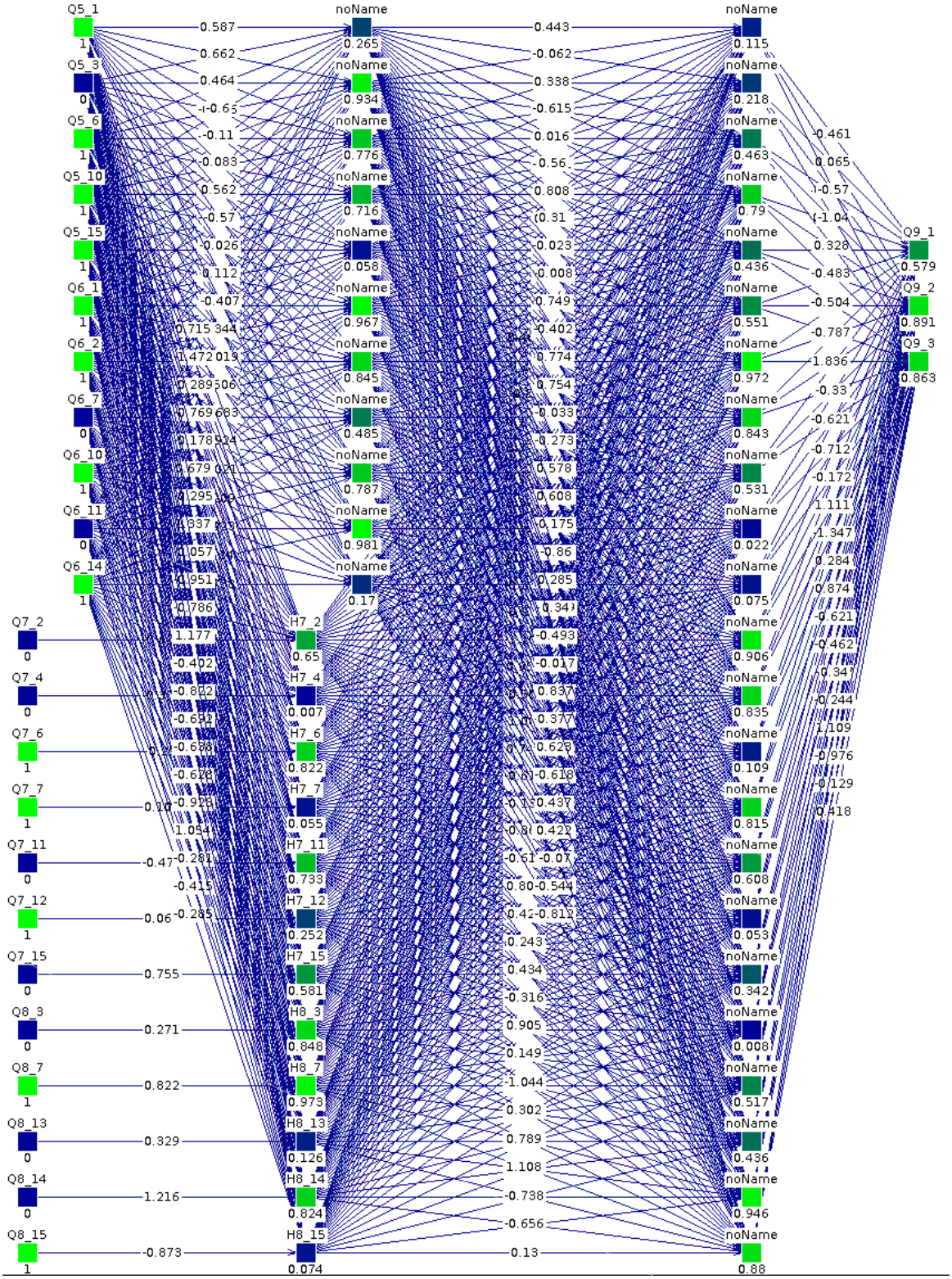
To verify this property of the network, we created a database of 100 surveys collected from hypothetical opinion makers. In practice, the database structure was formed by 5 sets of variables: 1) n.5 strengths, 2) n.6 weaknesses, 3) n. 7 opportunities, 4) n. 5 threats, 5) n. 3 outputs. Variables related to SWOT (a total of n.23 inputs) were randomly generated (within a range 0.1-0.9). In order to ensure a total consistency of each of the output value, the following formula to calculate them was applied:

$$Output = \Sigma S - \Sigma W + \Sigma (\Sigma S \cdot Oi) - \Sigma (\Sigma W \cdot Tj) \qquad (1)$$

The output value has been normalized between the open interval $\{x: 0<x<1\}$

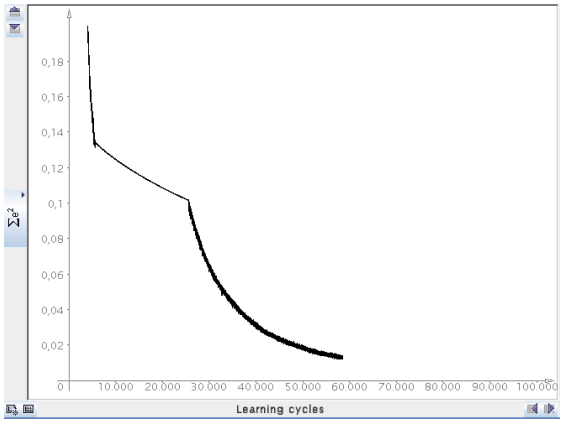
Subsequently, the network has been trained by using the SNNS Stuttgart Neural Network Simulator, developed by Zell et al. (1992). Training was performed on all 100 cases, to achieve the over-training of the network, aiming at the minimizing the error between the real and the estimated output values. This was obtained after 60,000 learning cycles, by using the standard back-propagation algorithm (eta=0.02, dmax=0.05; initial weights randomly distributed between the open interval $\{x: -1<x<+1\}$; topological order as updating learning function). The error graph is reported on Figure 3.

Figure 2: Structure of the network



Note: Cells from Q5_1 to Q6_14 are Strengths or Weaknesses, while from Q7_2 to Q8_15 are Weaknesses or Threats. Finally, Q9_1, Q_9_2 and Q9_3 are outputs.
Source: own elaborations

Figure 3. Error graph showing the network training



Note: Y axis represent the sum of square error, while the X axis represent the number of iterations.
Source: own elaborations

The network was purposely trained to achieve an overfitting or overtraining which, despite leading to a poor generalization of data, it is capable to learn data "by heart" (including the noise of the data). In this way, by modifying each input value (ceteris paribus), it is possible to verify whether its contribution is positive or negative to the output. Therefore, consequently to a marginal reduction of each variable(δ, for δ>0), it is possible to verify the consistent changes of the values corresponding to outputs:

a) $S - \delta$, then $\Delta Output<0$

b) $W - \delta$, then $\Delta Output>0$

c) $O - \delta$, then $\Delta Output<0$

d) $T - \delta$, then $\Delta Output>0$

We performed 23 simulations (one for each input variable), and all results confirmed the expected outcomes. As it is shown in Table 1, the average on all impacts on the values of output variable are coherent and consistent with the hypotheses.

Table 1. Changes on three output caused by a 0.10 reduction of original SWOT variables

	Output 1	Output 2	Output 3
Strengths			
S1	-5,92%	-5,96%	-5,80%
S2	-4,64%	-4,74%	-4,72%
S3	-4,07%	-4,02%	-4,13%
S4	-2,70%	-2,74%	-2,74%
S5	-4,48%	-4,58%	-4,53%
Weak.			
W1	3,10%	3,16%	3,15%
W2	2,99%	2,99%	2,94%
W3	3,37%	3,44%	3,40%
W4	3,41%	3,42%	3,37%
W5	2,64%	2,66%	2,68%
W6	2,02%	2,03%	2,06%

	Output 1	Otput 2	Output 3
Opp.			
O1	-1,69%	-1,75%	-1,70%
O2	-1,07%	-1,11%	-1,01%
O3	-1,00%	-0,97%	-1,01%
O4	-1,92%	-2,00%	-1,93%
O5	-2,09%	-2,06%	-2,09%
O6	-1,22%	-1,17%	-1,20%
O7	-0,13%	-0,13%	-0,14%
Thr.			
T1	2,06%	1,99%	2,04%
T2	3,22%	3,21%	3,18%
T3	4,46%	7,01%	2,45%
T4	7,50%	7,46%	7,45%
T5	2,78%	2,71%	2,67%

Source: own elaborations

4.3. DATA COLLECTION

An online survey was submitted to 3 groups of experts and opinion leaders interested in the promotion of agroenergy technology in the province of Foggia, involved in the 7th FP-REGPOT project:

- group A: scientists and experts of the University staff, engaged in the project;

- group B: scientists and experts of the University staff, aware of the above project, but not directly involved in the project;

- group C: scientists, experts and opinion makers interested in the development of the agroenergy technology, but not belonging to the University.

The survey was submitted by email through the complete mailing list of the three groups of people who were committed (i.e. 27 of group A) or involved (15 of group B, and 11 of group C) by the project. A brief summary of the questions and answers is provided in Table 2, while the description of the variables is reported in Box 1.

Table 2. Identification of SWOT variables resulting from the email survey

Strength	Weaknesses	Opportunities	Threats	Expected evolution of the project
Q5_1 (A,B)	Q6_1 (A,B)	Q7_1 (B)	Q8_2 (C)	Q9_1 (A,B)
Q5_3 (A,B)	Q6_2 (A,B)	Q7_2 (A,B,C)	Q8_3 (A,B,C)	Q9_2 (A,B)
Q5_4 (B)	Q6_5 (B)	Q7_3 (C)	Q8_5 (B,C)	Q9_3 (A,B)
Q5_6 (A,B)	Q6_7 (A)	Q7_4 (A,B)	Q8_6 (C)	
Q5_10 (A,B)	Q6_10 (A,B)	Q7_5(C)	Q8_7 (A,B,C)	
Q5_11 (B)	Q6_11 (A)	Q7_6 (A)	Q8_13 (A)	
Q5_13 (B)	Q6_12 (B)	Q7_7 (A,B,C)	Q8_14 (A,B)	
Q5_15 (A)	Q6_13 (B)	Q7_8(C)	Q8_15 (A,B)	
	Q6_14 (A)	Q7_10(C)		
		Q7_11 (A)		
		Q7_12 (A,B)		
		Q7_15 (A,C)		

Note: in parentheses is reported the group which identified each item
Source: own elaborations

Box 1. List of SWOT variables and expectations

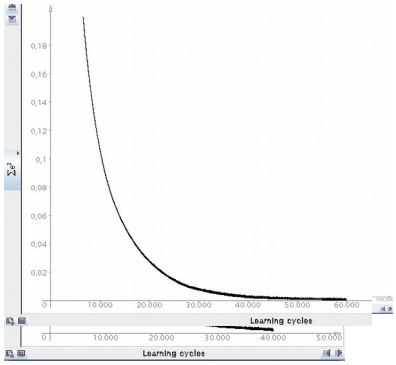
I) STRENGTHS
Q5_1: Team working on innovative research topics
Q5_3: Team's technical research coupled with socio-economic/sustainability considerations
Q5_4: Scientific and technical excellence of the Team
Q5_6: Multi- and inter-disciplinary Team composition
Q5_10: Well-equipped Facility Centre established
Q5_11: Team linked with the University
Q5_13: Involvement of local, regional and other stakeholders
Q5_15: HORIZON 2020 EU Programme launching in 2014
II) WEAKNESSES
Q6_1: Team's employment time horizon limited by the project
Q6_2: End of project affecting research financing
Q6_5: Work risks and uncertainties due to STAR's innovative character
Q6_7: Major Team's publications in prestigious journals yet to appear
Q6_10: Public administration bureaucratic effects delaying actions
Q6_11: Team's location (Foggia) lacking research tradition/reputation
Q6_12: Regional and other policy-related uncertainties
Q6_13: Regulation barriers, e.g. for utilization of wastes

Q6_14: Institutional and practical problems for the follow-up situation
III) OPPORTUNITIES
Q7_1: Favourable developments at global level, e.g. collaboration with emerging countries
Q7_2: Favourable developments at EU level, e.g. new regional/innovation policies
Q7_3: Favourable developments at national level, i.e., exodus from present crisis
Q7_4: Favourable developments at regional level, e.g., "smart specialization" in Apulia region
Q7_5: Favourable developments at the local level, e.g., related initiatives by local actors
Q7_6: Upgrade of the strategic role of energy security, with attention at Agro-Energy
Q7_7: Further growth of environmental concerns, with attention at "green" solutions
Q7_8: Establishing sustainability criteria across many sectors of the EU economies
Q7_10: Proper recognition of the strategic role of soil in the agro-food-biomass agenda
Q7_11: Recognition of Bioeconomy as a key driver for development of Southern Europe
Q7_12: Biobased economy's positive effects to revitalize local economies
Q7_15: Symbiotic effects from education and training, e.g. new Master and Erasmus actions
IV) THREATS
Q8_2: Unfavourable developments at EU level, e.g. a crisis of the Union/Eurozone
Q8_3: Unfavourable developments at national level, i.e., prolongation of present crisis
Q8_5: Unfavourable developments at the local level, e.g., lack of related initiatives by actors
Q8_6: Critical for implementation/followup "gaps" of knowledge, new risks and uncertainties
Q8_7: Financial difficulties for supporting research and innovation
Q8_13: Lack of recognition of Bioeconomy as a key driver for development
Q8_14: Unfavourable demographic trends keeping away competent persons for careers/studies
Q8_15: Weak or negative social acceptance by stakeholders and society
V) OUTPUTS – "*Do you think the STAR*Agro Energy group will be able to*":
Q9_1: create the conditions for the development of new business on bioeconomy in the next 10 years
Q9_2: strengthen a research group capable to offer technical solutions for local and EU challenges
Q9_3: create a strong network at international level, for research and business excellence

5. RESULTS

The three sets of data were used to train three different networks. The training has been conducted by using the standard back-propagation algorithm (*eta*=0.02, *dmax*=0.05; initial weights randomly distributed between the open interval {x: -1<x<+1}; topological order as updating learning function). The error graphs corresponding to the networks related to groups A, B, and C after, respectively, 60,000, 40,000 and 80,00 iterations, are reported on Figure 4.

Figure 4. Error graphs following the networks training



Note: Y axis represent the sum of square error, while the X axis represent the number of iterations. From left to right, training of networks referred to groups A, B, and C are shown.
Source: own elaborations

In order to analyse the structure of the network, and to evaluate the contribution of each input variable in the output value, simulations have been performed by subtracting (ceteris paribus) 0.10 to the original value of every SOWT variable. Each network simulated the outcome for each respondent.

The output changes, measured relatively to the original value, and expressed in percent, are reported in Table 3, Table 4, and Table 5. It is worth noting that in several cases the outcome of the simulation is not consistent with the expected outcomes stated in the hypotheses. For the sake of simplicity, we counted the number of occurrences of inconsistency within the three groups (see Table 6).

Table 3. Changes on three output caused by a 0.10 value reduction of SWOT variables – Group A

	Output 1	Output 2	Output 3
Strength			
Q5_1	-2,65%	-0,39%	2,87%*
Q5_3	-0,65%	-1,85%	-2,28%
Q5_6	-5,09%	-2,36%	-6,12%
Q5_10	3,55%*	-1,25%	-1,33%
Q5_15	3,55%*	-1,25%	-1,33%
Weak.			
Q6_1	-0,70%*	0,07%	-3,85%*
Q6_2	3,60%	-1,01%*	1,31%
Q6_7	3,57%	1,53%	1,83%
Q6_10	3,60%	-1,25%*	-0,07%*
Q6_11	-0,31%*	1,26%	1,95%
Q6_14	1,93%	0,22%	-0,69%*

	Output 1	Otput 2	Output 3
Opp.			
Q7_2	-0,18%	0,06%*	0,02%*
Q7_4	-0,16%	-0,10%	0,15%*
Q7_6	-0,46%	-0,20%	0,09%*
Q7_7	-0,14%	0,14%*	0,60%*
Q7_11	-0,43%	-0,32%	-0,50%
Q7_12	-0,95%	-0,07%	-0,24%
Q7_15	-0,24%	-0,03%	0,40%*
Thr.			
Q8_3	-0,16%*	0,09%	-0,08%*
Q8_7	-0,60%*	0,81%	0,83%
Q8_13	1,10%	-0,21%*	1,35%
Q8_14	-0,26%*	-0,21%*	-0,08%*
Q8_15	3,55%	-1,25%*	-1,33%*

Note *) lack of consistency
Source: own elaborations

Table 4. Changes on three output caused by a 0.10 value reduction of SWOT variables – Group B

	Output 1	Output 2	Output 3
Strength			
Q5_1	-3,32%	-2,46%	-2,24%
Q5_3	-2,23%	1,10%*	-0,77%
Q5_4	-1,39%	-0,48%	-0,83%
Q5_6	1,78%*	-0,93%	-1,69%
Q5_10	-2,16%	1,10%*	3,60%*
Q5_11	2,38%*	-0,36%	-0,15%
Q5_13	-3,05%	-2,30%	-3,24%
Weak.			
Q6_1	3,42%	3,63%	1,94%
Q6_2	-1,70%*	-2,97%*	-1,80%*
Q6_5	2,34%	0,09%	0,78%
Q6_10	-1,07%*	-0,92%*	-0,12%*
Q6_12	-1,58%*	-1,98%*	-2,12%*
Q6_13	0,25%	-0,48%*	-0,33%*

	Output 1	Otput 2	Output 3
Opp.			
Q7_1	0,50%*	0,29%*	0,74%*
Q7_2	-0,02%	-0,02%	-0,01%
Q7_4	0,74%*	1,29%*	1,05%*
Q7_7	1,10%*	1,21%*	1,09%*
Q7_12*	0,08%*	0,05%*	0,05%*
Thr.			
Q8_3	-0,07%*	0,00%	-0,03%*
Q8_5	0,03%	0,08%	0,15%
Q8_7	0,26%	-0,08%*	-0,27%*
Q8_14	0,17%	0,11%	0,04%
Q8_15	-0,26%*	0,00%	0,58%

Note *) lack of consistency
Source: own elaborations

Table 5. Changes on three output caused by a 0.10 value reduction of SWOT variables – Group C

Opp.	Output 1	Output 2	Output 3
Q7_2	-0,41%	1,42%*	0,01%*
Q7_3	0,44%*	-0,24%	0,37%*
Q7_5	0,99%*	0,13%*	0,26%*
Q7_7	-7,07%	5,21%*	1,05%*
Q7_8	0,85%*	2,50%*	-0,06%
Q7_10	3,82%*	4,14%*	3,24%*
Q7_15	0,05%*	-0,03%	-0,04%

Threats	Output 1	Otput 2	Output 3
Q8_2	-4,13%*	-0,32%*	-3,04%*
Q8_3	-0,01%*	-0,18%*	0,00%
Q8_5	0,57%	-1,74%*	-0,78%*
Q8_6	4,92%	-1,06%*	-3,32%*
Q8_7	-8,37%*	2,14%	-1,30%*

Note: *) lack of consistency. Since participants of Group C do not have a sufficient information on the details of the agroenergy initiative, the were not asket about Strengths and Weaknesses.
Source: own elaborations

Table 6. Comparison of number of inconsistent occurrencies among the three groups

	Strengths	Weaknesses	Opportunities	Threats	Total
Group A	3/15=20%	7/18=39%	7/21=33%	9/15=60%	26/69=38%
Group B	5/35=14%	10/18=56%	12/15=80%	5/25=20%	32/93=34%
Group C	-	-	15/35=43%	11/25=44%	26/60=43%

Source: own elaborations

According to our elaborations, all groups exhibited a certain degree of inconsistency of between the logical relationship of SWOT factors and their expectations. Surprisingly, Groups A and B exhibited the same degree of inconsistency, probably due to the fact that they shared a similar degree of information. On the contrary, participants of Group C exhibited a higher degree of inconsistency, probably due to a lower capacity of grasping the general context situation of agroenergy, and the limited capacity to express a consistent level of expectation.

6. CONCLUSIONS

In this study we proposed a methodology based on a feed-forward neural network, capable to represent and compare the knowledge detained by different groups of people regarding the development of a small-scale agroenergy conversion plants in rural areas. By comparing the different structure of knowledge of the three groups, it is possible to measure the degree of convergence (or divergence) among their knowledge.

The representation of the knowledge is in most of cases of qualitative nature, so it is hard to use to perform analysis, comparison, and simulations. Therefore, our methodology may favourite the debate and support the strategic planning of innovative projects in rural areas.

The application of neural network models is still a novel field in the domain of rural studies. There is a great potential, as participatory approaches are considered very important especially to favourite the extraction of embedded knowledge detained by local actors, which may be particularly relevant at the early stage of an innovation, where the scarcity of information may increase the uncertainty and risk perception of actors involved.

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