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Social Acceptance Optimization of Biomass Plants: a Fuzzy Cognitive Map and Evolutionary Algorithm Application

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Implementation of biomass plants is often thwarted by public opposition, despite potential technical-economic and normative feasibility. This opposition is generally known as NIMBY effect. One of the most adopted political action able to overcome or to control NIMBY effect is the information of population about ex-ante and ex-post characteristics of the intervention. However, the informative approach is a complex task to achieve. In this process, several ecological, social, normative and economic variables must be properly considered in a unique framework. Moreover, the selection of variables on which concentrate information and the time consumption of knowledge transfer, seem to be additional issues to solve. Thus, the aim of the research is to implement and verify an innovative procedure to assess and minimize the potential NIMBY effect in case of planning of biomass facilities. From the methodological point of view, this study combines Fuzzy Cognitive Map (FCM) procedure and nonlinear modelling solved by the Social Cognitive Optimisation (SCO) evolutionary algorithm. This work focuses on the perception of experts in bioenergy sector about Combined Heat and Power (CHP) plant. The proposed methodology is developed for a theoretical case study in Tuscany (central Italy).

1. Introduction

Facility siting of biomass plants and their acceptance are opposed and debated in several situations worldwide. As stated by Jenssen (2010) “acceptance can be understood as an affirmative or tolerating attitude towards a specific fact”. It could be represented as a result of a personal (Jenssen, 2010) or social (Maggi et al., 2013) cost/benefit analysis. In these terms the so-called NIMBY (Not In My Back Yard) effect represents a decrease in facilities acceptance due to a worsening of cost/benefit analysis. The characteristics and presence of NIMBY effect in a population can be examined by means of a within-subjects and between-subjects approaches (Terwel et al., 2012). The first one highlights subjective features of a single person, whereas the second one depicts the influence among different subjects and external circumstances (e.g. accidents, media coverage, etc.). Both approaches are useful to picture the situation of local stakeholders perception and to share participated processes for biomass plant implementation. A certain difficulty in the acceptance/opposition assessment of facilities, and in particular of biomass plants, is however showed in international literature due to both lack of unambiguous terminological statement and complexity of methodology. In fact, the term NIMBY is often debated because of its stigmatization by supposedly selfish stakeholders (van der Horst, 2007), its use to discredit often well-founded objection, and its limitation to local population perception (Devin-Wright, 2011). In addition, it’s worth noting how many procedures of biomass plants acceptance evaluation are present in literature. For example, many studies are centred on several methodologies mainly focused on questionnaire-based interviews, focus groups, qualitative analysis (see e.g. Schweizer-Ries, 2008), and spatial based approaches (van der Horst, 2007). Common suggestions for acceptance maximisation seem to be the informing involved stakeholders about both ex-ante and ex-post characteristics of intervention, as well as bottom-up approach. This participative approach is, however, quite complicated to carry out because of the involvement of several socio-economic and environmental peculiarities interrelated in a holistic way. Additional difficulties seems to be the prioritization of concepts which stakeholders are to be informed about, as well as the optimization of time-consuming information strategies. Thus, a quantitative and objective methodology to overcome the above-mentioned limits is needed. An innovative methodological approach was thus defined in this paper, developing a three-step procedure. First, through a between-subjects approach, the concepts involved in biomass plants acceptance were defined and related to each other by means of Fuzzy Cognitive Map (FCM). FCM was designed and calibrated after a detailed literature analysis. Then, a questionnaire-based within-subject analysis was implemented to validate FCM and to assign importance (weights) to different concepts and relations. Finally, the last phase deals with optimizing the process of informing stakeholders to maximize acceptance of the examined theoretical biomass plant. Priority of variables on which information is to be concentrated was assessed by a nonlinear programming (NLP) procedure solved by a Social Cognitive Optimization (SCO) evolutionary algorithm. The whole methodological approach is described in section 2. Section 3 illustrates main results, while last section gives general discussion and conclusions of main findings.

2. Methodology

2.1 Fuzzy Cognitive Map implementation

Different studies have investigated biomass plants acceptance. Their methodological approach mainly focuses on the definition of variables and parameters perceived as the most important by stakeholders. Literature seems to lack in the evaluation of relationships among these variables. This may lead to a latent information emerging in the interviews due to the absence of correlation among those concepts influencing social acceptance. Hence, FCM technique was here adopted for the analysis of biomass plants perception.

FCM represents a graphical structure derived from network theory (Kosko, 1986). The elements of a FCM can be depicted in concepts (the nodes of a graph) and relationships among nodes (described by arrows). FCM can be implemented by the application of two methods: i) analysis of literature data or ii) interviews carried out to focus groups or single individuals. Both the quantification of the concepts, and the value of relations are generally defined by means of fuzzy logic, as well as conversion of qualitative linguistic evaluators in numerical terms. FCM or single concepts can be described by several indexes identified by Özesmi and Özesmi (2004). Among the indexes considered by these authors, the "centrality" value was evaluated in this paper. Centrality shows the connection's strength among variables, in relation with the weight of the variables. In other words, it gives information about how a criterion contributes within the FCM. The FCM was implemented as follows. Firstly, concepts and relations among concepts linked to biomass plants acceptance were pointed out through a detailed literature analysis focusing on non-technical barriers (Rösch and Kaltschmitt, 1999), innovation issues (Negro et al., 2012), as well as comprehensive analysis of the system related to biomass planning (Upreti and van der Horst, 2004). Then, after designing FCM, concepts and relations were quantified as well as validated by interviews to bioenergy experts. Quantification was based on the conversion of verbal assessment based on a 3-scale, as proposed by Chen and Hwang (1992), for both positive and negative correlations. Unless FCMs were already applied in the bioenergy sector and biomass plant evaluation (Lopolito et al., 2011), the innovation of this study consists in the optimisation of FCM by a NLP model, as reported in the following section.

To test the methodology, a theoretical case study was implemented. The analysis focuses on the perception of Combined Heat and Power (CHP) biomass plant hypothetically planned for a mountainous area of central Italy (Tuscany Apennine).

2.2 Maximisation of social acceptance for biomass plant

FCM represents a typical nonlinear system due to the presence of causal correlations, feedbacks and loops. Thus, optimisation of FCM can be carried out by a NLP model. In this paper the term "optimisation" stands for "maximisation of biomass plant acceptance". Maximisation was defined by partition of information among FCM concepts (e.g. in terms of time to dedicate to each concept in a knowledge transfer procedure).

FCM can be described as an iterative process according to Eq(1) (Papageorgiou et al., 2011):

$$C_{i,k} = \sum_{i} C_{i,k-1} \cdot w_{j,i} \tag{1}$$

where $C_{i,k}$ is the value of concept i at iteration k and $w_{j,i}$ is the value of the link between driver concept j and receiver concept i.

If all concepts of FCM reach a stabilisation then they are at a steady state. At a steady state, the variables can tend to zero, increase/decrease exponentially, have a cyclic stabilization or have a stabilization at a constant value (Kok, 2009). Steady state is the reference value for the analysis of the concepts and the achievement of FCM optimization for acceptance maximization.

Some attempts of FCM optimization have already been introduced in literature. These studies are mainly based on the Differential Evolution (DE) algorithm (Storn and Price, 1997). Among the examined studies, that by Papageorgiou and Groumpos (2005) shows a hybrid method to optimize FCM; this method is based on the DE algorithm as well as on the nonlinear Hebbian rule. An optimal FCM weight matrix was achieved applying the DE and the Sequential Quadratic Programming (DE-SQP) algorithms (Shou et al., 2012). DEPS, an hybridation of the Particle Swarm optimization and the DE, was also applied to obtain the above mentioned purpose (Parsopoulos et al., 2004). Xie et al. (2002) introduced a Social Cognitive Optimisation (SCO) algorithm to solve NLP models. This algorithm is based on social cognitive theory, a direct evolution of genetic and particle swarm-based evolutionary computational techniques. More specifically, SCO is an optimization model based on the observational learning mechanism in human social cognition. Xie et al. (2002) highlighted how SCO seems to have higher performances when compared with previous NLP techniques. In addition, according to author knowledge, SCO has never been applied to solve FCM. Thus SCO algorithm was here tested to solve the following optimisation model – Eq(2).
Let A_k be the value of acceptance concept at iteration k (where all concepts are at their steady state), the objective function of the model will be:

$$\begin{aligned}
&MAX\,(A_k)\\
&s.t.\\
&w_{inf,p}\left[0,1\right]\\
&w_{inf,n}\left[-1,0\right]\\
&w_{inf,p}+\left|w_{inf,n}\right|=1
\end{aligned} \tag{2}$$

where $w_{inf,p}$ is the influence (weight) of information concept on a specific positive variable p and $w_{inf,n}$ is the influence (weight) of information concept on a specific negative variable n. For the case study, positive and negative concepts correspond to parameters that increase or decrease acceptance, respectively.

3. Results

The implemented FCM is composed by 49 concepts (included the concept “acceptance”) and 102 correlations among concepts (Fig.1).
The weight (importance) of each concept in the FCM was computed in two phases. First, the quantification of importance took into account the literature concerning the specific concept and the perception of experts. In this step, through the procedure explained in Özesmi and Özesmi (2004), the weight of each variable was computed as centrality index. The following parameters seemed to be the most central: power of the plant, presence of agreements and associations in the bioenergy sector, economic efficiency of the local bioenergy chain, supply of biomass, and adequate logistics (Tab.1). Lower values of centrality were showed for the following concepts: information process carried out by mass media, presence of industrial areas, smell of the biomass plant, availability of wood residues from agricultural pruning, and risk perception.
In the second phase, the partition of information among concepts was computed. The partition value represents the attention to be given to each concept in a theoretical learning process (e.g. public seminars, workshops or focus groups). This value comes from the optimization of FCM to maximize “acceptance” variable. Even if a certain correlation between centrality index and optimised partition of information among concepts was recorded (corrected R^2: 0.62), significant differences in the ranking of these parameters were highlighted (Tab.1). In fact, in an optimized scenario local stakeholders’ characteristics (participation of local stakeholders in bioenergy chain, agreements and associations in local bioenergy chain, adequate bioenergy demand, stakeholders' skills) seemed to reach higher values when compared with other parameters. More specifically, lower values were reached by territorial peculiarities such as presence of arable lands, need of Short Rotation Forestry, and competition among current agricultural practices and bioenergy production. This is probably due to the small percentage of agricultural land in the case study area (mainly covered by forests), as well as the resulting low importance attributed to these concepts by experts.
Worth of noting is the result which arises from the analysis of: i) social and technical-economic concepts, and ii) environmental and health-related concepts. The examination of both the centrality index and the partition of information stressed how social and technical-economic concepts are the most important in both cases. Indeed, for CHP plant implementation, experts of bioenergy sector most likely perceived fewer environmental risks and potential health damage in respect to different local stakeholders, or population. This can be due to consolidated knowledge of experts about CHP technology and its impact.

From a methodological point of view, despite the high number of FCM correlations as well as the ten iterative cycles necessary for concepts' stabilisation, the SCO algorithm showed good performances. Resolution of objective function (Eq.1) was reached in a relative short computational time also with a low number of internal SCO algorithm agents (size of library and size of swam) (Xie et al., 2002).

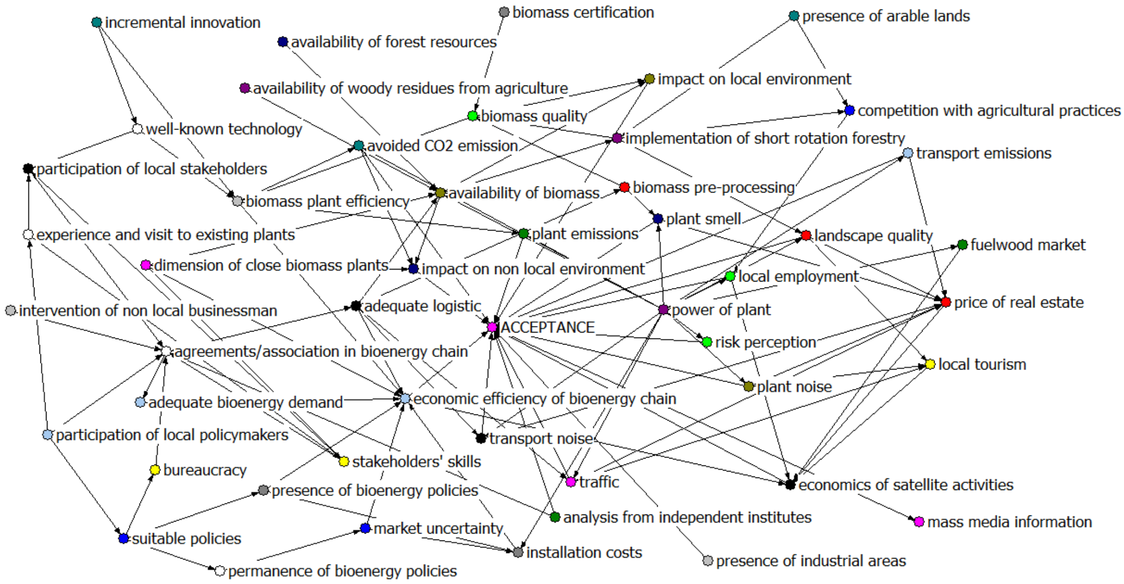

Figure 1: Fuzzy Cognitive Map (graphical elaboration developed by means of NetDraw software - Borgatti, 2002)

Table 1a: FCM concepts, centrality index, partition of information and relative ranking (in brackets)

**: social and techno-economic concepts, **: environmental and health-related concepts*

Concept	Centrality	Partition of information
Power of plant*	6.63 (1st)	2.92 % (17th)
Agreements/association in bioenergy chain*	5.76 (2nd)	3.18 % (2nd)
Economic efficiency of bioenergy chain*	5.28 (3rd)	3.14 % (10th)
Availability of biomass*/**	4.96 (4th)	0.90 % (41th)
Adequate logistic*	4.76 (5th)	2.05 % (26th)
Biomass plant efficiency*/**	4.50 (6th)	3.17 % (5th)
Participation of local stakeholders*	3.15 (7th)	3.19 % (1st)
Biomass quality*/**	3.13 (8th)	3.11 % (13th)
Installation costs*	2.94 (9th)	3.01 % (16th)
Economics of satellite activities*	2.82 (10th)	3.09 % (14th)
Stakeholders' skills*	2.74 (11th)	3.17 % (4th)
Implementation of Short Rotation Forestry*	2.69 (12th)	0.62 % (44th)
Price of real estate*	2.64 (13th)	2.36 % (24th)
Landscape quality**	2.52 (14th)	2.67 % (21th)
Well-known technology*	2.24 (15th)	3.15 % (6th)
Local tourism*	2.20 (16th)	2.53 % (23th)
Traffic**	2.11 (17th)	0.32 % (46th)
Dimension of close biomass plants*	2.02 (18th)	0.23 % (47th)
Presence of bioenergy policies*	2.02 (19th)	3.15 % (7th)
Avoided CO_2 emission**	2.02 (20th)	1.77 % (30th)
Experience and visits to existing plants*	1.93 (21th)	3.12 % (12th)
Suitable policies*	1.86 (22th)	1.36 % (33th)
Market uncertainty*	1.82 (23th)	1.41 % (32th)
Biomass pre-processing*/**	1.72 (24th)	3.12 % (11th)
Adequate bioenergy demand*	1.63 (25th)	3.18 % (3rd)

Table 1b: FCM concepts, centrality index, partition of information and relative ranking (in brackets)

**: social and techno-economic concepts, **: environmental and health-related concepts*

Concept	Centrality	Allocation of information
Impact on non local environment**	1.50 (26th)	1.53 % (31th)
Permanence of bioenergy policies*	1.42 (27th)	1.23 % (36th)
Transport noise**	1.39 (28th)	1.33 % (34th)
Participation of local policymakers*	1.36 (29th)	3.15 % (9th)
Plant emissions**	1.33 (30th)	2.71 % (20th)
Incremental innovation*	1.33 (31th)	1.13 % (39th)
Bureaucracy*	1.31 (32th)	2.91 % (18th)
Presence of arable lands*	1.21 (33th)	0.07 % (48th)
Fuelwood market*	1.11 (34th)	2.02 % (27th)
Local employment*	1.08 (35th)	2.83 % (19th)
Impact on local environment**	1.00 (36th)	0.54 % (45th)
Transport emissions**	0.89 (37th)	0.71 % (42th)
Competition with current agricultural practices*	0.86 (38th)	0.67 % (43th)
Availability of forest resources*/**	0.81 (39th)	1.78 % (29th)
Plant noise**	0.65 (40th)	1.20 % (37th)
Intervention of non local businessman*	0.61 (41th)	3.02 % (15th)
Biomass certification**	0.50 (42th)	2.59 % (22th)
Analysis from independent institutes*	0.39 (43th)	3.15 % (8th)
Risk perception**	0.39 (44th)	1.97 % (28th)
Availability of woody residues from agriculture*	0.28 (45th)	1.15 % (38th)
Plant smell**	0.27 (46th)	0.99 % (40th)
Presence of industrial areas*	0.00 (47th)	1.26 % (35th)
Mass media information*/**	0.00 (48th)	2.15 % (25h)

4. Discussion and Conclusions

In this paper, an innovative method for the maximisation of biomass plant acceptance was developed. The model provide an optimisation of FCM based on the SCO algorithm in a NLP procedure. A theoretical case study, focused on bioenergy experts' perception about planning of CHP plant in a rural area of Tuscany (central Italy), was developed. The results compared a traditional FCM indicator of importance for concepts (i.e. centrality index) and innovative ones (i.e. best partition of information among concepts in the learning process). Though a significant correlation resulted between centrality and optimal partition of information, ranking of concepts for both indexes was quite different. The optimization procedure stressed how, according to experts' perception, a communication procedure would be mainly focused on the characteristics of local stakeholders and on organisational peculiarities of the bioenergy chain. Indeed, thanks to rigorous national and local regulations about environmental and health-related topics, a low risk for these variables was perceived by bioenergy experts. Different results and the arising of perceived risk for local environmental impact and pollution could be probably highlighted by carrying out interviews to the local population, as frequently reported in international literature.

The presented model could be a useful tool for perception analysis of different biomass plant typologies (or, possibly, other facilities). Different socio-economic, normative, and territorial issues as well as different classes of stakeholders, can be considered for the evaluation. The optimization of public debate and informative procedure can be also reached with the proposed method. This aspect could be important for the application of regulation statement recently implemented at regional level. In fact, by the approval of the law n. 46/2013 "Public debate and promotion of regional participation for formulation of regional policies and local regulations" (Tuscany Region, 2013), Tuscany recognized and introduced, for the first time in the Italian legislation, the mandatory nature of the Public Debate on public works and interventions having specific costs.

However, to make the model a useful decision support system, additional evaluation as well as the implementation of real case studies should be carried out. More specifically, future lines of research should focus on: i) qualitative and quantitative differences among stakeholders' perception, ii) comparison between FCM-NLP model and other methodologies in the same case study, iii) evaluation of uncertainty related to FCM system and communication strategies. Optimisation of FCM could be analysed and compared for both SCO algorithm and additional algorithm application (e.g. DE-SQP and DEPS).

Eventually, agent-based sensitivity analysis should be developed in order to define performance trends of the SCO algorithm.

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