Environmental Science and Pollution Research (2019) 26:35288–35304
https://doi.org/10.1007/s11356-019-05506-2

ADVANCES & PROSPECTS IN THE FIELD OF WASTE MANAGEMENT

Exploring social determinants of municipal solid waste management: survey processing with fuzzy logic and self-organized maps

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Received: 25 February 2019 / Accepted: 16 May 2019 / Published online: 28 May 2019

Abstract

In the present study, the establishment of decision-making criteria and a novel and robust interdisciplinary approach for systematically characterizing effects of uncertainties in social determinants of municipal solid waste management using an important fuzzy logic methodology is demonstrated. The primary goal is to highlight the social benefits of this waste management option such as job creation, hygiene and health protection, and working safety as well as to indicate certain side effects occurring during waste processing (odor and leachate production, social trust). The current research is based on a social survey in an agro-industrial region, Thessaly, Greece, and indicates a set of diversified key factors that are related to public acceptance of municipal waste management schemes. These features are input to Kohonen Self-Organized Maps (a special type of Artificial Neural Networks) for clustering residents according to their social perception and attitudes in terms of solid waste collecting and recycling. Both analyses highlight the environmental concern, social perception, hygiene and health, economic status, and lifestyle as the primary social determinants in affecting the public attitudes towards recycling. In both cases, these soft computing techniques seem to outperform the classical statistical and logical regression methodologies and become very promising in accurately predicting waste management practice and possibly other environmental behaviors.

Keywords Municipal solid waste management · Social determinants · Survey · Classification · Fuzzy logic · Self-organized maps

Nomenclature

Notation	Definition
FL	fuzzy logic
MSW	municipal solid waste
SOM	self-organized maps
ANN	artificial neural network
ECGB	environmental concern and general behavior
SPHH	social perception hygiene and health
ESLF	economic status and lifestyle
GB	general behavior
SP	social perception attitudes and beliefs
HH	hygiene and health protection
BD	behavior determinants towards waste production
LF	lifestyle
A_{mean}	mean answer of all available data
GB_{mean}/A_{mean}	ratio of mean-GB over A_{mean}
SP_{mean}/A_{mean}	ratio of mean-SP over A_{mean}
HH_{mean}/A_{mean}	ratio of mean-HH over A_{mean}
BD_{mean}/A_{mean}	ratio of mean-BD over A_{mean}
LF_{mean}/A_{mean}	ratio of mean-LF over A_{mean}

Responsible editor: Philippe Garrigues

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Introduction

Due to the implementation of relevant environmental legislation, the amount of municipal solid waste (MSW) sent to landfills has been decreasing in the last years, the collecting of recyclables keeps increasing, and also household composting has lately started to take place. However, despite the improvement of recovery performance and quality of recycled materials, sustainable MSW management still remains a relatively complicated procedure involving multiple environmental and socio-economic criteria at the top of the agenda (Moustakas and Loizidou 2018; Turcott Cervantes et al. 2018).

Surveys appear to be helpful tools regarding the role of social stakeholders' behavior and awareness for effective decision-making in a sustainable environmental management process. For instance, perception and attitudes of residents in townships with various climate change vulnerabilities were found to affect their behavioral intentions with regard to climate change adaptation and disaster risk (Lee et al. 2018). In order to contribute to greenhouse gas emissions reductions, various social research tools can provide an understanding of several factors influencing and shaping public support for the implementation of carbon capture and storage technologies, which represents an increasingly urgent priority (Braun et al. 2018; Karayannis et al. 2014). Moreover, for improving the public's awareness of urban air pollution and promote the establishment of more efficient policy for pollution control and climate change mitigation, employees' perceptions of air pollution and their willingness to pay taxes for improved quality were investigated (Liu et al. 2016).

Particularly, several questionnaire-based surveys focus on the level of knowledge and attitudes of people towards various waste management issues. Residents showed relatively high environmental awareness and willingness to pay for solid waste management (Song et al. 2016). A more specific aim can be to distinguish the key motivational drivers for encouraging households' participation in a "no plastic campaign" (Afroz et al. 2017). Also, social behavior was identified to be the most significant reason for pharmaceutical disposal leading to the generation of pharmaceutical wastes (Zorpas et al. 2018). People's attitudes and behavior regarding the problem of massive illegal dumping of construction waste are also important in order to gain awareness towards construction waste minimization (Liu et al. 2018). Even in managing contaminated sites, the role of understanding the different needs and attitudes of social stakeholders is critical to indicate effective remediation policies (Stezar et al. 2014). Generally, public support appears to be a key factor for the implementation of waste management schemes, along with technological advancement and ecological impact in a holistic approach (Lakioti et al. 2017). Conclusions and suggestions derived from social surveys may be used to improve people awareness for waste minimization and recycling behavior and promote enhanced public education and environmental protection campaigns in the framework of sustainable environmental management policies.

There is not a crisp measured tool set to use in order to obtain precise measurements of social determinants in solid waste processing and recycling. This is due to the fact that the most important impact evaluation techniques require the existence of diverse variables for estimation, which must be converted to a unified scale that measures the method quality. Furthermore, sometimes, there is not a descriptive technique to include many of these impact variables as key performance indicators, which also makes these variables to introduce a high degree of uncertainty and inaccuracy. For that reason, the use of soft computing techniques is preferable in producing adequate solutions in a multi-criteria analysis approach. Even though these methodologies are mostly applied in computer science problems, they have shown very promising performance in various interdisciplinary problems. Among this variety of tools, neural networks, fuzzy logic (FL), self-organized (Kohonen) maps (SOM), and probabilistic (Bayesian) neural networks are the most promising. In the current work, the important issue of social determinants estimation on urban waste management is quantitatively addressed by illustrating the computational ability of FL and SOMs methodologies.

FL was introduced by Zadeh (1965, 2008) as a methodology based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based. FL aims to represent expert knowledge in a rule-based style in order to build a standard control law that faithfully reflects this knowledge (Mamdani and Assilian 1975; Yen and Langeri 1999). According to (Zadeh 2008), FL's dynamics are twofold: (a) FL is able to provide rational decision-making, even under uncertainty, partiality of truth and value imprecision, and (b) FL performs adequately in multidisciplinary tasks that do not need crisp measurements and exact value computations hence similarly to multi-criteria analysis (Munda 2004; Munda 2008).

Due to its intrinsic characteristics, FL has already been employed in many applications, especially in control engineering, modeling, and systems analysis, but also in biomedical and hydrological studies among others (Nadiri et al. 2019; Ostadi et al. 2019; Akintola et al. 2018; Singh et al. 2006). Especially for engineering problems, FL proves to be the most promising alternative due to its distinct property to deal with imprecise input. Although research efforts using FL theory to deal with interdisciplinary problems of fuzzy input span among many fields, however, there is very limited research reported in literature relative to the qualitative evaluation of the social impacts regarding a specific environmental process (Kokkinos et al. 2018). Moreover, for social determinants' evaluation on municipal solid waste management practice, the research literature becomes far more limited.

In the present work, a FL-based decision support tool is proposed, which is able to set up all the measurable parameters affecting the process of waste collecting and recycling while at the same time focusing on the social attributes along with this methodology. The research is based on the results of a residents' survey in an agro-industrial region, Thessaly region, Greece, involving a set of diversified key factors that are related to public perception, attitudes, and acceptance of municipal waste management schemes. These attributes are input to Kohonen SOMs that are able to cluster residents according to their behavior on solid waste management, using the neural network–based pattern analysis. After the defuzzification process (see following chapters), this method succeeds to determine the overall social impact with a quantitative characterization: i.e., it is able to predict the future adoption of waste recycling by quantitatively and indirectly calculating the residents' perception of the topic. In both aforementioned analyses, the scope of the study is to highlight the principal components of social perception that are responsible in boosting attitudes towards waste recycling and at the same time to provide a quantitative order of these determinants indicating the ones with the highest impact.

The *novelty* introduced in this study is trifold, as it incorporates in important municipal solid waste management issues a social science methodology and a set of artificial intelligence methods that are able to provide adequate results when pure statistical or numerical theories cannot meet this challenge.

Materials and methods

Basics of fuzzy inference systems

In the description of a problem using FL, the *variables* may be linguistically described by a fuzzy set. However, linguistic variables are occasionally unable to fully express a whole fuzzy scale. For this reason, adjectives or adverbs are added to modify their values (very, low, medium, etc.). *Fuzzification* operations that map the above values into fuzzy membership functions (inclusions or exclusions from a fuzzy set) are used. Exactly on the inverse procedure, *de-fuzzification* operations map fuzzy membership functions into "crisp" output using fuzzy-type if–then rules. These rules create a robust knowledge representation scheme where the output is a consensus of all of the inputs making the FL system to adequately respond even when input values are not available or not trustworthy. The importance of each rule in the rule base can dynamically change, so that the degree to which each rule affects the output values can be controlled. FL processes elements of a *fuzzy set*, which are taken from a universe of discourse according to the fuzzy set theory using *membership functions* (Çolak and Kaya 2017).

Given a finite set of objects, E described as $E = \{e_1, e_2, e_3, \ldots e_n\}$ assumes a membership function of e_i to be denoted as mf_i. A *fuzzy set A* is defined as a linear combination of the e_i and mf_i terms: $A = \{mf_1(e_1), mf_2(e_2), mf_3(e_3), \ldots, mf_n(e_n)\}$. An important component of a FL system apart from the fuzzy set is the *fuzzy rule base* that consists of the "if–then"-type rules. Rule learning is achieved from the perspective of finding a favorable balance between the accuracy of the system, the speed required to learn the rules, and, finally, the interpretability of the rule bases obtained (Duţu et al. 2018). FL systems accept inputs that are initially given to the *fuzzification inference unit*. With the involvement of the *knowledge base*, the input variables are first compared with the membership functions on the antecedent part to obtain the membership values of each linguistic label. At the next step, the qualified consequents or each rule depending on the firing strength above are generated and, finally, the qualified consequents are aggregated to produce a crisp output (see Fig. 1).

Membership functions

For a fuzzy set A on the universe of discourse X, a *membership function* is defined as $\mu_A{:}X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1 (Lee 1996). This value is called the *degree of membership* and quantitatively describes the membership of the element of X into the fuzzy set A. Membership functions can be easily depicted in a planar graph with x-axis to be the space of discourse and y-axis the membership degree within the interval [0, 1]. The method of producing three of the most popular membership functions and their corresponding graphical illustrations are shown in Figs. 2 and 3.

Basic operations

The fuzzy logic operations, which are analogous to the classical logic ones, are the union, intersection, and complement:

- Union: assuming μ_A and μ_B are any two membership functions relating to fuzzy sets A and B respectively, the union of A and B is a fuzzy set defined by the membership function:

  $$\mu_{A \cup B}(x) = \mathrm{MAX}(\mu_A(x), \mu_B(x)).$$

- Intersection: assuming μ_A and μ_B are any two membership functions relating to fuzzy sets A and B respectively, the intersection of A and B is a fuzzy set defined by the membership function:

  $$\mu_{A \cap B}(x) = \mathrm{MIN}(\mu_A(x), \mu_B(x)).$$

- Complement: assuming μ_A is a membership function relating to fuzzy set A, the complement of A is a fuzzy set defined by the membership function:

  $$\mu_{A^c}(x) = 1{-}\mu_A(x).$$

Basics of SOM

SOMs are a special type of artificial neural networks (ANN) that use the methodology of unsupervised learning for training

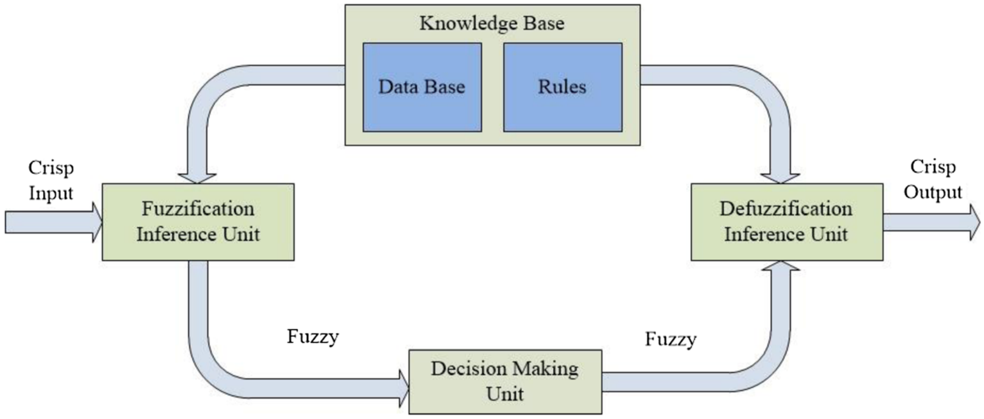


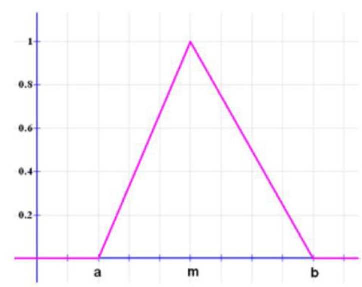
Fig. 1 Components of a typical fuzzy inference system

in order to produce a two-dimensional space topographic map of the input space, preserving the following properties: (a) the spatial location and distance of the output neurons directly correspond to a specific characteristic drawn from the input space and (b) incoming information from the input space is organized in such a way to preserve its proper context/neighborhood. Thus, the difference of SOMs to traditional ANN is that they use this method of the closeness or the neighborhood function to show the input space features and not the method of step-by-step fine-tuning or correction of the error using for example backpropagation.

The primary goal when creating a SOM is firstly to identify each of the corresponding signal patterns (features) of arbitrary dimension and convert them by reducing their

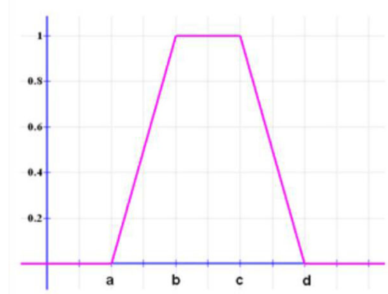
Triangular membership function: defined by a lower limit a, an upper limit b, and a value m, where $a < m < b$.

$$\mu_A(x) = \begin{cases} 0, & if \;\; x \le a \\ \dfrac{x-a}{m-a}, & if \; a < x \le m \\ \dfrac{b-x}{b-m}, & if \; m < x < b \\ 0, & if \; x \ge b \end{cases}$$



Trapezoidal membership function: defined by a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, where $a < b < c < d$.

$$\mu_A(x) = \begin{cases} 0, & if \;\; (x < a) \; or \; (x > d) \\ \dfrac{x-a}{b-a}, & if \; a \le x \le b \\ 1, & if \; b \le x \le c \\ \dfrac{d-x}{d-c}, & if \; c \le x \le d \end{cases}$$



Gaussian function: defined by a central value m and a standard deviation $k > 0$. The smaller k is, the narrower the “bell” is.

$$\mu_A(x) = e^{-\frac{(x-m)^2}{2k^2}}$$

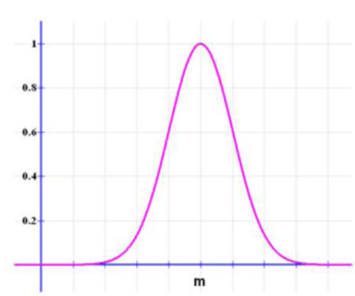


Fig. 2 Graphical illustrations of the most popular membership functions

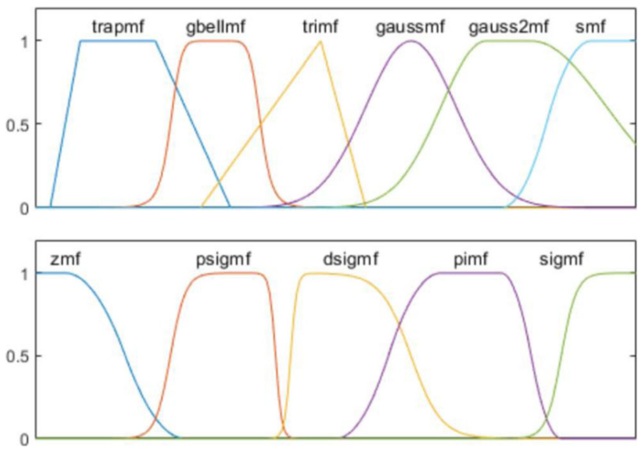


Fig. 3 Graphical illustrations of all the membership functions in the MATLAB® fuzzy toolkit

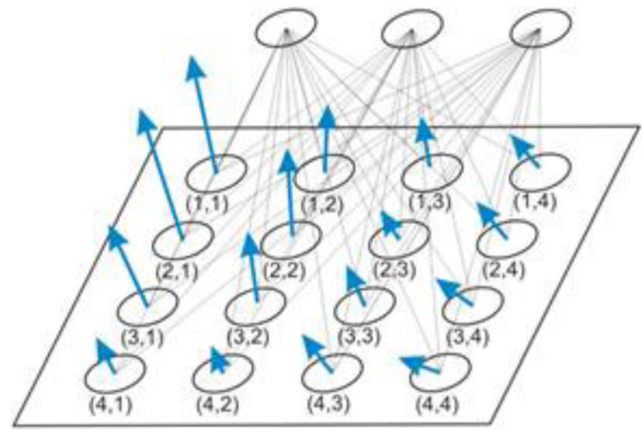


Fig. 4 A typical 2D-lattice of a SOM

dimensions into a one- or two-dimensional topographically ordered map. Each one of the nodes in a SOM represents a weighted vector and also the pair of (x, y) coordinates of the node within the two-dimensional lattice. Note that the input features are also represented as a vector of the same dimensions. In this way, what node corresponds to the closest-match can be computed based on a distance measure, using the aforementioned vector weights. Once the best/closest matching node is calculated, the area surrounding the "best" node is optimized, so that this region now represents the cluster in which the input vector belongs. This process is repeated many times until equilibrium or rather a stabilization of the clusters is reached. The steps to be taken for the learning process of SOMs are the following (Kaya et al. 2016; Hong et al. 2003; Kohonen 1998, 2001, 2013, 2014; SOM in Matlab (2014):

- The nodes' weights are randomly initialized.
- Out of the training data, a vector to be presented to the SOM is randomly selected.
- The best matching node, i.e., the node with its weights to be closest to the input vector, is calculated.
- The region surrounding the best matching node is reorganized shrinking each time to fine-tune the system.
- The weights of all nodes are adjusted inside in each cluster and especially those closer to the best matching node.
- Finally, the whole process is repeated up until stabilization of the system is reached.

More specifically, the aforementioned learning process is rigorously illustrated as follows (Lin and Chen 2005): let $X = [x_1, x_2, \ldots, x_M]^T$ be the input layer to the SOM as a vector of M-neurons, with the output neurons to be a set of N items ($u_j, j = 1 \ldots N$) organized as a 2D-lattice, as shown in Fig. 4.

Let also $W = \{w_{i,j} \mid i = 1 \ldots M, \quad j = 1 \ldots N\}$ be the weights assigned from input layer neuron to the output layer neuron. After all weights have been initialized to small random numbers, then the network is triggered to calculate the distance between the input vector X and the weight vector W_j, and this must be calculated for each neuron u_j. This distance is defined to be the Euclidean distance and it is used as the similarity measurement between the weight vector and the input vector:

$$d_j = \|X - W_j\| = \sqrt{\sum_{i=1}^{M} (x_i - w_{ij})^2}$$

The application of this algorithm on the SOM creates a topological map where dark areas illustrate the subset of neurons that belong to the same cluster according to the abovementioned similarity criteria (see Fig. 5). In order to take advantage of a SOM when data is fed to this neural network, we need to group together all items that belong to the same cluster. The two methodologies that have been proven to provide near optimal clustering are the *hierarchical agglomerative clustering* and the *partitive clustering using k-means.* Using the first technique, a hierarchy of clusters is built using a "bottom-up" approach where each data observation starts in its own cluster, and as we move up, the hierarchy clusters are merged into bigger ones. On the opposite side, partitive clustering is a prototype-based model, where prototypes are separating boundaries according to a concise description of a characteristic of the original data set, and this leads to the construction of each cluster. Many prototypes can be applied (hyperplanes, hyperspheres, etc.), forming a variety of clustering algorithms. Agglomerative clustering is obtained from clustering trees (otherwise called dendrograms), where K-means constructs a spherical cluster, as denoted by:

$$S = \sum_{i=1}^{C} \sum_{x \in Q_i} \|x - c_i\|^2$$

where C is the set of clusters and c_i is the centroid of the cluster Q_i.

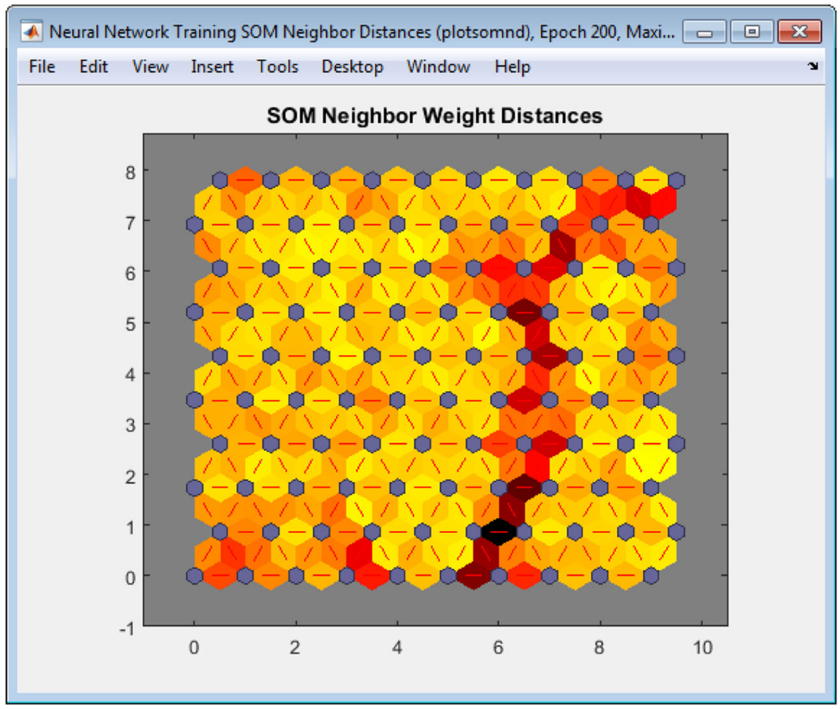


Fig. 5 An example of the SOM neighborhood weight distances

MSW case study and analysis using FL and SOM

Case study and survey

In 2018, a survey was conducted to identify the social perceptions of collecting recyclables and composting biowastes as major procedures for practicing MSW management in an agro-industrial region, Larissa city, Thessaly, Greece. After a pilot study was carried out to verify the validity of the questions, a survey was conducted into the greater residential body of the city. The survey targeted primarily the homeowners and old-time residents, and also university students on a secondary preference. Note that such surveys start with the bias that a "pro-green" methodology and behavior is mentioned, and therefore it is likely to be considered highly acceptable by most of the people regardless of their broader environmental concerns. The survey collected 327 anonymous responses, with 23 responses to have incomplete or outlier answers, thus leaving 314 valid data items. The questionnaire was designed to cover the issues of general behavior, social acceptance, hygiene and health protection, attributes of behavior towards waste production, and lifestyle apart from several general demographic attributes that relate to age, gender, educational level, and economic status. A compendious view of the distributed questionnaire is provided in Table 1.

All answers on the questions Q1 to Q22 were framed on a five-point Likert scale acting in accordance with a generalized data treatment for the fuzzification process of the responses and allowing a unified methodology in analyzing inference for categorical and numerical data using chi-square tests. Initial findings from the responses (see Fig. 6a–f) showed 240 responders that have adopted recycling in every aspect of their life, while the rest of 74 responders have answered negatively to the corresponding question.

It must be noted here that the design of the questionnaire was based on questions similar to those used in the questionnaires of De Fao (2014) and Milutinovic et al. (2016), trying to achieve results from our processing methodology that will be compatible with the aforementioned. Furthermore, in our analysis, the predetermined fact is included that the measurement of the social acceptance impacted by the composting process cannot be assessed by one survey question or even a cluster of those. The reason for this determination is the fact that people usually agree for the proposed "green" technologies but, when they are asked to implement them, they are rather reluctant. The questions Q20–Q22 are the most significant questions of the survey, as, via them, responders are classified into two groups of (i) adopters and (ii) non-adopters of the recycling behavior. It is of high importance that there is a significant difference in the way that the three perception variables imposed by Q20–Q22 affect the two subgroups of participants as Fig. 6 a–f illustrate.

Application of FL to residents' social acceptance and adaptation to recycling

The fundamental aspects in the development of a FL model consist of the individual construction of the following modules: (a) identification of the fuzzy sets involved, i.e., sets with smooth boundaries and to what these set correspond; (b) inclusion of appropriate linguistic variables, i.e., variables whose values have

Table 1 Condensed version of questionnaire

General and Demographic Characteristics					
Gender	□ **Male**	□ **Female**			
Age (inscribe)	________________				
Have you adopted recycling		□ *Yes*	□ *No*		
Educational Level	□ Low	□ Elementary	□ Secondary	□High	□Highest
Economic Status	□ Low	□ Medium	□ Medium to High	□High	□Very High
General Behavior					
Q1	Relates to residence status (available space, gardens, etc.)				
Q2	How the increase of recycling helps to preserve natural resources				
Q3	How much recycling recharges positively the environment				
Q4	Measure the avoidance of buying products with excessive and unnecessary packaging				
Q5	Measure the frequency of buying "disposable" products				
Q6	Measure the social benefits emanated from the recycling process				
Q7	Measure the environmental expanses produced by recycling				
Social Perception Attitudes and Beliefs					
Q8	Visual Impact Assessment				
Q9	Potential for the Creation of New Jobs				
Q10	Indirect impact on the Employment Quality				
Q11	Risk Perception (Not only Health)				
Hygiene and Health Protection					
Q12	Smell impact				
Q13	Residue generation				
Q14	Treatment capacity				
Behavior Determinants towards Waste Production					
Q15	Usefulness of waste prevention				
Q16	Average production of waste per capita				
Q17	Average recycling of bio-waste per capita				
Lifestyle					
Q18	Belief that increasing recycling is an indispensable change in the lifestyle of individuals.				
Q19	Belief that the increase of recycling while reducing the consumption of natural resources is fundamental contribution of each of us.				
Decision-Making for Adopting Recycling					
Q20	"How much would the *Environmental Concern and General Behavior Characteristics* affect your decision to adopt recycling?"				
Q21	"How much would the *Social Perception and Hygiene and Health Characteristics* affect your decision to adopt recycling?"				
Q22	"How much would the *Economic status and Lifestyle* affect your decision to adopt recycling?"				

their corresponding representative fuzzy set that describes their quantity and quality characteristics; (c) variable value and possibility distribution, i.e., the inclusion of all the repressions, constraints, and liberties that a linguistic variable can take when a fuzzy set is assigned to it; and (d) the set of fuzzy inference rules in the form of (if–then), which succeed to describe the functional mapping of a logic formula, as the vague attributes and labels of the linguistic variable are transformed into standard mathematical values. This model has been proven to demonstrate substantial improvements in data analyses achieving accurate deductions.

For the case study described in the "Case study and survey" subsection and relatively to the identification of the fuzzy set of value involved in the questionnaire responses, all questions from Q1–Q22 are set up to include answers in Likert scale where (1 = Very Low, 2 = Low, 3 = Medium, 4 = High, and 5 = Very High) are the corresponding equivalent fuzzy values on the linguistic variables imposed by the questions.

For the fuzzy model we try to build here, we concentrate on the questions Q20–Q22 that define how the adaptation of recycling emanates from the influence of (a) environmental concern and general behavior, (b) social perception hygiene and health, and (c) economic status and lifestyle. Note that we chose the above three perception linguistic variables, because they summarize all the attributes and determinants of all the questions in the survey, as these questions have been classified according to these perceptions. Furthermore, out of the six possible categories of determinants, as they have been separated in the questionnaire, we choose to pair up perceptions and finally end up with three basic perception linguistic variables. The reason we choose to do so it that we significantly

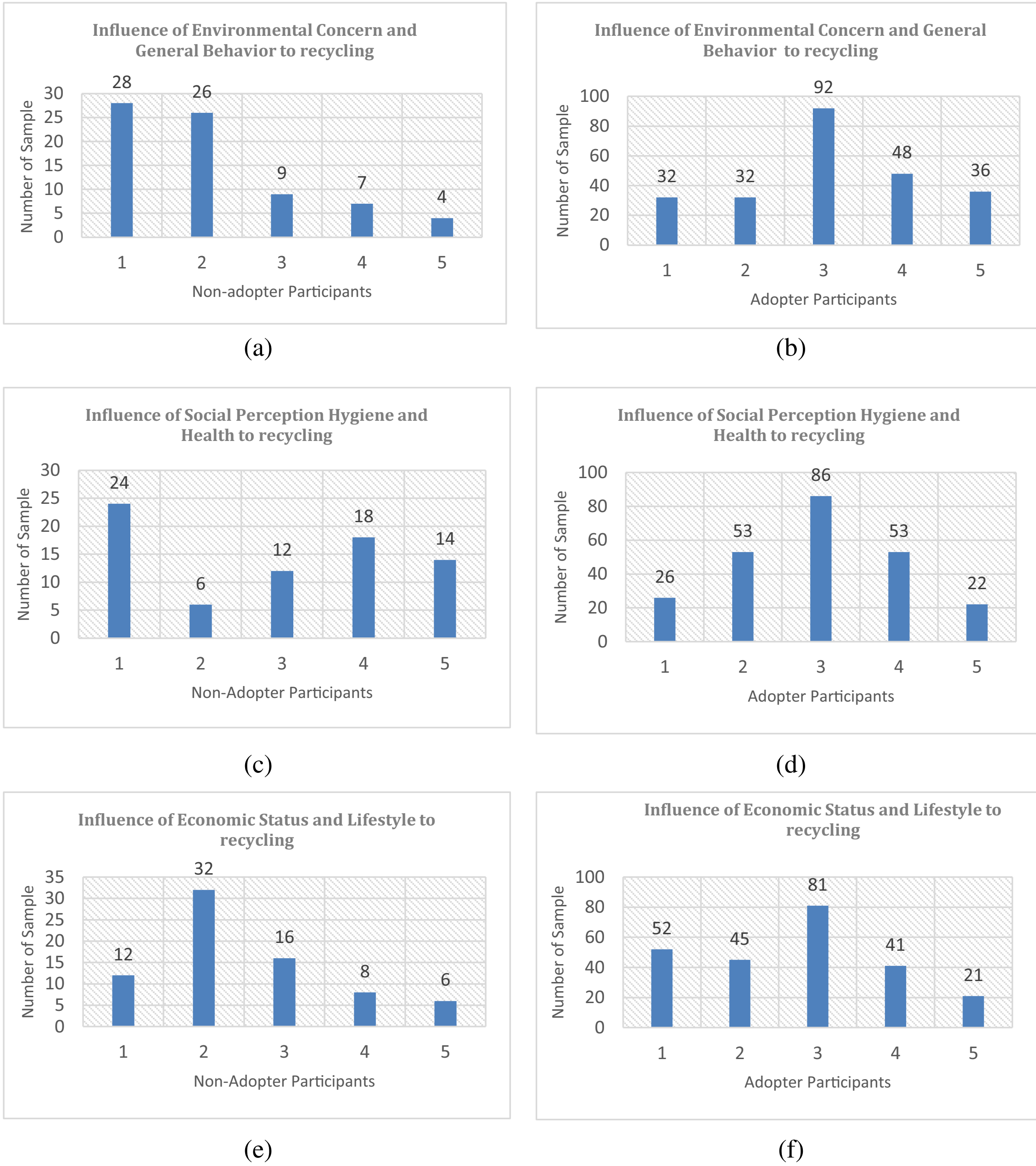


Fig. 6 Distribution of non-adopters (**a**, **c**, **e**) and adopters (**b**, **d**, **f**) to recycling relative to the criteria imposed by questions Q20–Q22 of the survey

decrease the number of linguistic input variables in the fuzzy model, keeping the construction of if–then rules a rather small process. On the other hand, the inclusion of six input variables on a FL system makes the process of creation of inference rules a rather complicated procedure due to its exponential nature. Additionally, the increase of the input variables prohibits the deep analysis of the system due to the exponential combinations of membership function types involved in a thorough analysis.

Our primary target is to evaluate the residents/responders social acceptance and adopting of recycling, by constructing a FL system and using the responses we received from the survey. We denote the linguistic variables described above as follows:

- ECGB = environmental concern and general behavior
- SPHH = social perception hygiene and health
- ESLF = economic status and lifestyle

We furthermore distinguish as $ECGB_a$, $ECGB_n$, $SPHH_a$, $SPHH_n$, $ESLF_a$, and $ESLF_n$ the above linguistic variables among the recycling adopter and non-adopter participants. The inputs into the FL system will be the combinations of the above six, while the output will be the adaptation of recycling technology or not, but in fuzzy terms of the abovementioned Likert scale spanning from Very Low to Very High. Figure 7 shows the method used: first a combination of input variables are fed into the FL system, which responds back with the output of affirmative, medium, or negative adoptability of recycling. In the case of positive output, we note the combination of the input values as well as the combination of the membership functions used for them. Otherwise (output is negative or of low confidence), membership functions and inference rules are changed. This fine-tuning of the system is continued until better results are achieved.

For both the distinct cases of adopters and non-adopters, we formulate a fuzzy set that is defined by a function that maps the corresponding objects in the survey (i.e., the beliefs B_a, $ECGB_n$, $SPHH_a$, $SPHH_n$, $ESLF_a$, and $ESLF_n$) to a domain of concern to their membership value in the set. As mentioned before, this is the membership function μ_A. The selection of the membership function for each of the inputs directly affects the outcome of the FIS even though the most popular functions include the triangular, the trapezoidal, the bell, and the Gaussian. Regardless of the membership function selection, the if–then logic inference rules are the ones that primarily define the reaction of the FIS to any combination of inputs having any combination of fuzzy values. Any rule that is added in the FIS carries: (a) a description, (b) an antecedent, (c) a consequent, (d) a weight, and (e) a connection in the network. For example "IF ECGB is low and SPHH is high and ESLF is high THEN Recycling_Adaptation (RA) is medium" is a rule that drives the behavior of FIS when the combination of fuzzy input is as noted. The construction of the rule set is based on the assumption that if ECGB, SPHH, and ESLF are scored high in the Likert Scale (1 = Very Low, 2 = Low, 3 = Medium, 4 = High, and 5 = Very High), then the acceptance of this methodology is considered to be high logically. Note that the five fuzzy values for each of the three inputs create a rule set of cardinality 5 × 5 × 5 = 125 rules. The outcome of each of the rules is based on the mean of the equivalent of the input values in the Likert scale and the rounding to the closest integer either up or down in the scale in the de-fuzzification process. The first part of the rule set (first 25 rules) for the case of (ECGB = Very Low) is given in Table 2. The rest of the rules are produced using the same methodology.

Three FIS were developed for the set of $ECGB_a$, $SPHH_a$, and $ESLF_a$ variables and another three for the set of $ECGB_n$, $SPHH_n$, and $ESLF_n$ variables corresponding to the use of the triangular, trapezoidal, and generalized bell functions. For each of the inputs and for each of the used membership functions, their parameters were set up accordingly. The same was held for the output variable for which the same configuration was used. In the following set of figures (Fig. 8), screenshots of the membership functions for each case and the 3D surface of the FIS outcome for the configuration of the triangular membership function are provided.

Segmentation and visualization of public opinions towards MSW processing, using SOM

In this subsection, SOMs are used to segment the public opinions towards MSW management processing. This segmentation can be done according to a variety of criteria (age, educational level, economic status, etc.). To discover distinct public orientations towards MSW management procedures, our methodology is

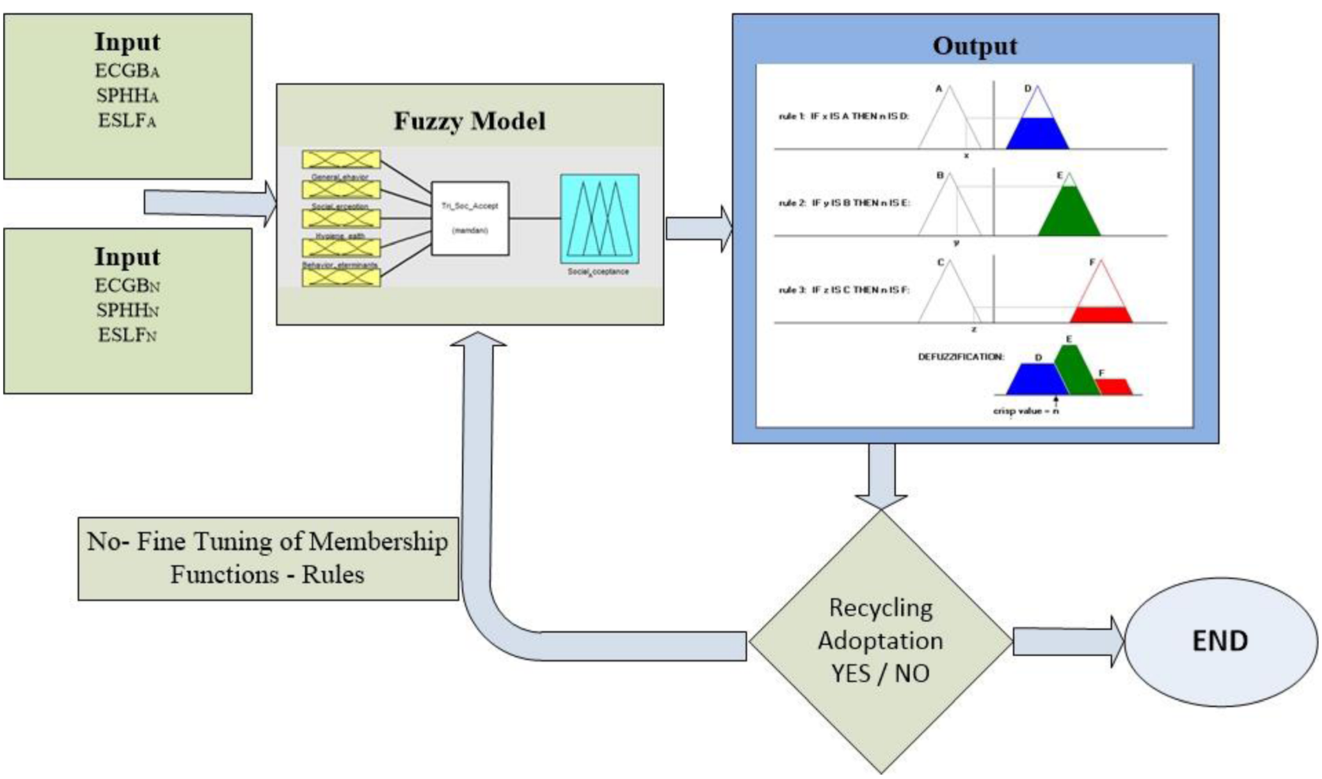


Fig. 7 FL system for recycling adaptation

Table 2 Part of the FIS if–then rule set

ECGB	SPHH	ESLF	RA
Very Low	Very Low	Very Low	Very Low
Very Low	Very Low	Low	Very Low
Very Low	Very Low	Medium	Low
Very Low	Very Low	High	Low
Very Low	Very Low	Very High	Low
Very Low	Low	Very Low	Very Low
Very Low	Low	Low	Low
Very Low	Low	Medium	Low
Very Low	Low	High	Low
Very Low	Low	Very High	Medium
Very Low	Medium	Very Low	Low
Very Low	Medium	Low	Low
Very Low	Medium	Medium	Low
Very Low	Medium	High	Medium
Very Low	Medium	Very High	Medium
Very Low	High	Very Low	Low
Very Low	High	Low	Low
Very Low	High	Medium	Medium
Very Low	High	High	Medium
Very Low	High	Very High	Medium
Very Low	Very High	Very Low	Low
Very Low	Very High	Low	Medium
Very Low	Very High	Medium	Medium
Very Low	Very High	High	Medium
Very Low	Very High	Very High	High

consisted of three stages: (a) to create a spatial model of the responses aggregated by the survey; (b) to select a specific number of fragments on the map, which correspond to representative attributes of the social acceptance characteristics referred in the questionnaire; and (c) to create profiles for these opinions/attributes. Taking the above steps in order, the creation of the SOM is basically the representation of respondent clusters into regions of a two-dimensional rectilinear space illustrating the similarity of opinions. SOMs can achieve nonlinear mappings from multi-dimensional data to a low-dimensional space (preferably two dimensional) while preserving all similarity relationships of the original data. The operation of the network is based on unsupervised learning to cluster the input vectors into regions that are defined depending on their Euclidean distance to already mapped vectors. This technique is best known by the name of ordered vector quantization. More specifically, for each questionnaire-answer sheet, a vector of all the answers (in Likert scale) is created. Following, these vectors are transformed creating ratios of opinions based on the average of answers A_{mean} using the aforementioned quantization. This organization allows ordering the resulted clusters of opinions forming reduced abstractions of complex data. In Table 3, the performance of FIS for both the adopter and the non-adopter case are included. In any case, the values in Table 3 represent averages either over the total adopter body (240) or the non-adopter body (74).

In order to determine the number of clusters, the questionnaire responses were grouped using the MATLAB *nnstart* software. The system has been run with a variety of training setups (epochs) and also a variety of values on the size of the two-dimensional map. For all cases, there were no clearly separated regions. A typical run is shown in Fig. 9a giving an unclear view of well-separated regions in the 6×6 map. To overcome this problem, *k-nn* clustering was additionally applied, which succeeded to reduce the number of initial neighborhoods into 5 as shown in Fig. 9b. The regions in Fig. 9b correspond to the clustering emanating from the input vectors that contain all the features described in Table 4. Note that some of the regions are bigger than others, while the number of hits in each region does not necessarily correspond in an analogous way. The hit count for each region is as follows: 1➔89, 2➔10, 3➔112, 4➔54, and 5➔49. However, we cannot be sure that the above clustering corresponds to crisp classes as these have been implied by the five-level Likert scale responses. We cannot induce for example that these five classes correspond to the five different educational levels in demographics for the survey.

To further deepen our intuition into the clustering information coming from this approach, it is useful to study the component planes that resulted from the SOM construction. These give more detailed information as to how data that contain some specific feature are distributed over the map, which in consequence affects the overall clustering process. In Fig. 10, an array of component planes is produced for each of the features as they have been determined in Table 4. Each one of these features indicates the contribution of the GB, SP, HH, BD, and LF categories of responses into the overall responses. They show, for example, that responders with low average on the responses overall GB_{mean}/A_{mean} (i.e., people that score higher than the average in the section of the General Behavior) are mapped on the top and right outer edges of the map, while participants that score on average less on the General Behavior features than the overall average of responses are mapped to the left and lower section of the map. Similar inferences can be done for each one of the five different features in Fig. 10, having always in mind that the darker the color of the SOM map is, the higher the value of the features is. These component planes need to be analyzed in parallel with the SOM map to identify the clusters as these are depicted in Fig. 9a and b.

Discussion of results

Performance of the FIS models

The various cases taken in the development of the FIS included both the adopters and the non-adopters of the recycling behavior

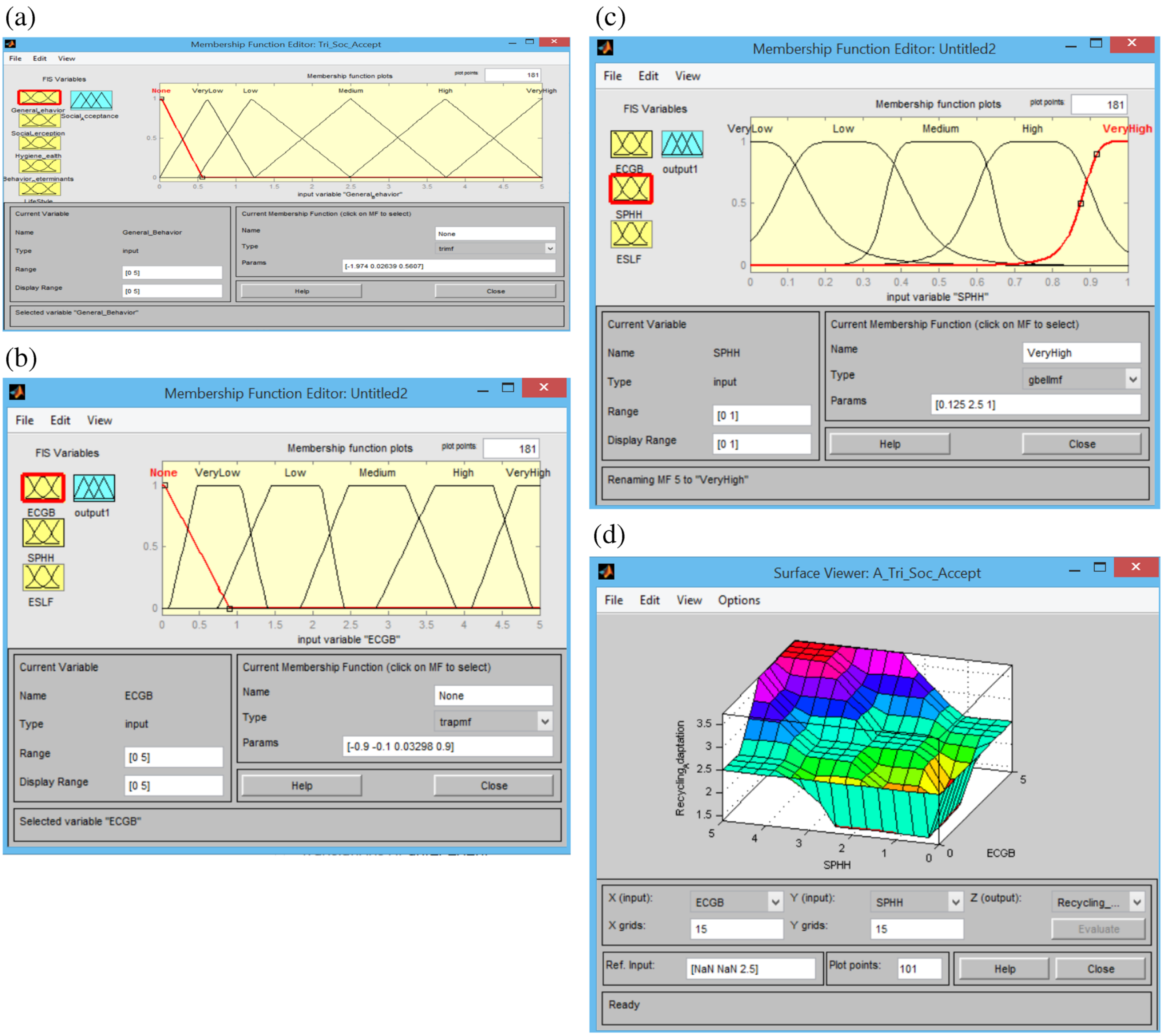


Fig. 8 **a** Triangular input MFs. **b** Trapezoidal input MFs. **c** Generalized Bell input MFs. **d** 3D Surface FIS outcome

and focused on how the environmental concern, the general behavior, the social perception, the hygiene, the health, the economic status, and the lifestyle of the responders affect this behavior. For this reason, similar responses were clustered and aggregated into three groups for both non-adopters and adopters, which were denoted as $ECGB_a$, $SPHH_a$, and $ESLF_a$, and $ECGB_n$, $SPHH_n$, and $ESLF_n$ accordingly. For both classes of responders, the same rule set for the FL system was used. Furthermore, a variety of membership functions was experimented with, spanning from triangular to trapezoidal and generalized bell. In all cases, the outcome of all FIS shows that fuzzy input is mapped through the membership functions close to 5 (i.e., equivalent to responses in Likert scale). Figure 8d illustrates this trend for two out of the three inputs, and the output again tends to reach the high values for high scoring in responses in the three classes. On the other hand, the processing of all questionnaires summarized in Table 3 shows the attitude of respondents towards recycling.

To ensure the scientific validity of the FIS methodology in predicting resident intentions relating to adopting recycling, all analyzed scenario outcomes have been clustered into 6 groups that recorded the $ECGB_a$, $SPHH_a$, and $ESLF_a$, and $ECGB_n$, $SPHH_n$, and $ESLF_n$ cases into separate spreadsheets. Based on these cases, several statistical tests were performed, by concentrating on the statistical significance of our simulation outcomes (Borror 2009), having as the main target to access the prediction of the FIS models depicted above. Thus, we deal with the statistical significance that is a valid estimate as to how close the outcome of the FIS models lie around the true statistics coming from the survey within a confidence interval. Common levels of reliability for newly introduced models are around the 95%

Table 3 Characteristic first level clustering from the survey

Characteristic (clustering from Table 1)	Notation	Adopter mean answer	Non-adopter mean answer	FIS output for adopter	FIS output for non-adopter
General behavior (questions Q1–Q7)	*GB*	2.980	2.134	–	–
Social perception attitudes and beliefs (questions Q8–Q11)	*SP*	2.912	2.762	–	–
Hygiene and health protection (questions Q12–Q14)	*HH*	3.015	2.736	–	
Behavior determinants towards waste production (questions Q15–Q17)	*BD*	2.878	2.311	–	–
Lifestyle (questions Q18–Q19)	*LF*	2.689	2.609	–	–
Environmental concern and general behavior (Q20)	*ECGB*	3.100	2.094	3.347	2.657
Social perception hygiene and health (Q21)	*SPHH*	2.966	2.891	3.128	3.003
Economic status and lifestyle (Q22)	*ESLF*	2.725	2.513	2.903	2.510
Mean answer of all available	A_{mean}	2.908	2.506	–	–

confidence, also written as $p = 0.05$, called the p-confidence level, even though there are research methodologies that signify their importance with a $p = 0.001$ confidence level.

Given the set of 314 distinct questionnaire responses, the means of 2.908 and 2.506 were calculated for the adopter and the non-adopter case and also the corresponding variances. However, what we focus on in parallel is the true mean (μ) of all the simulation tests. For this study, let us assume that the produced FIS models score Recycling_Adaptation (RA) outcomes distributed according to the normal distribution. Using this assumption, it is therefore implied that there is not any significant dependency between any RA output and all other RA outputs from previous FIS models. The fuzzy output of the FIS model cannot produce the true mean μ and the variance σ^2, thus, the distribution of fuzzy outcome cannot be modeled with the normal distribution. Instead, the Student's t-distribution (Gosset 1908) can be used, which similarly tries to approximate the normal distribution when the input is of large quantities (Fig. 11). As Krzywinski and Altman (2013) as well as Fay and Proschan (2010) indicate, the functional mapping between the proposed 95% confidence interval $[x-d, x+d]$ and the probability q can be obtained by performing an integration over the approximate normal distribution. Nevertheless, in our case, the data is not significantly large, thus the solution does not exist in a closed form, and instead we can use numerical methods.

In Appendix Table 5, the pair correlations are shown for SURVEY statistics taken from the questionnaires and the FIS statistics taken over the adopter case and non-adopter case simulations. The Pearson's, Kendall's tau_b, and Spearman's_rho correlation tests in the screenshots taken from SPSS (SPSS, © ver 20, Chicago, USA) are provided. Note that Pearson's test gives a significant correlation of $p = 0.05$ where the other two reach also a significant correlation of $p = 0.01$.

This allowed also performing non-parametric pairwise sample t tests between the SURVEY statistics and the FIS model statistics that span from 95 to 99% confidence intervals

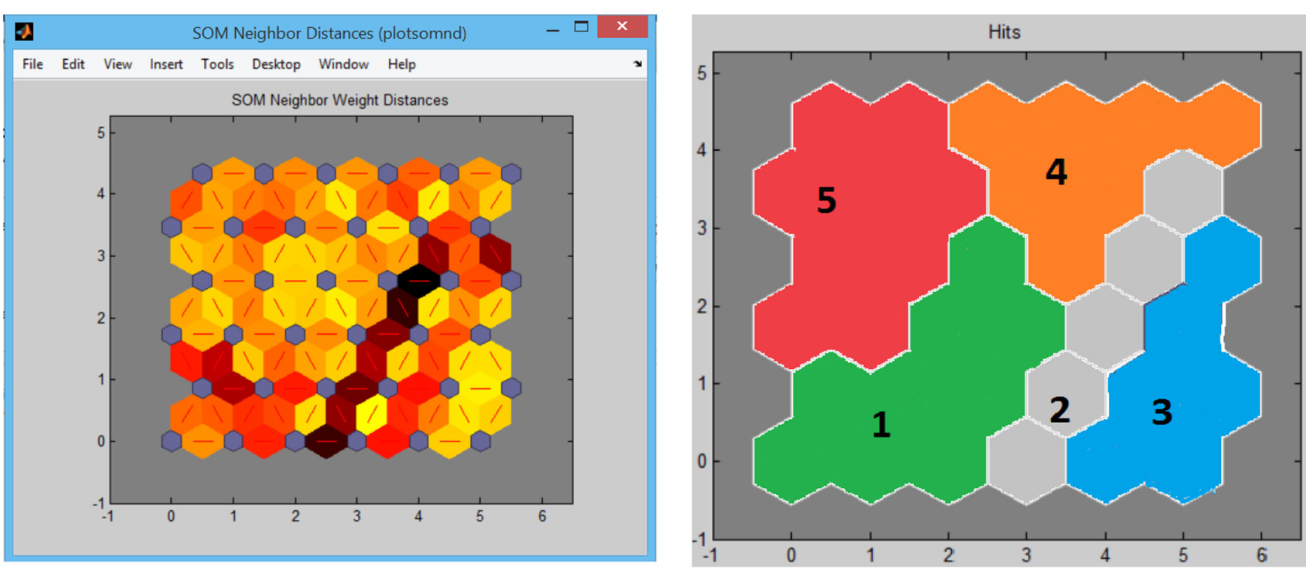


Fig. 9 **a** Typical SOM run for 6 × 6 map and **b** 5-nn clustering after the SOM application

Table 4 Features used in the input vectors of SOM

Input vector feature	Notation
Mean answer of all available data	A_{mean}
Ratio of mean: GB over A_{mean}	GB_{mean}/A_{mean}
Ratio of mean: SP over A_{mean}	SP_{mean}/A_{mean}
Ratio of mean: HH over A_{mean}	HH_{mean}/A_{mean}
Ratio of mean: BD over A_{mean}	BD_{mean}/A_{mean}
Ratio of mean: LF over A_{mean}	LF_{mean}/A_{mean}

justifying the statistical significance of our model. Appendix Table 6 shows the mean, the standard deviation, and the standard error mean indicating that the upper and lower bounds remain the same only fluctuating the t values.

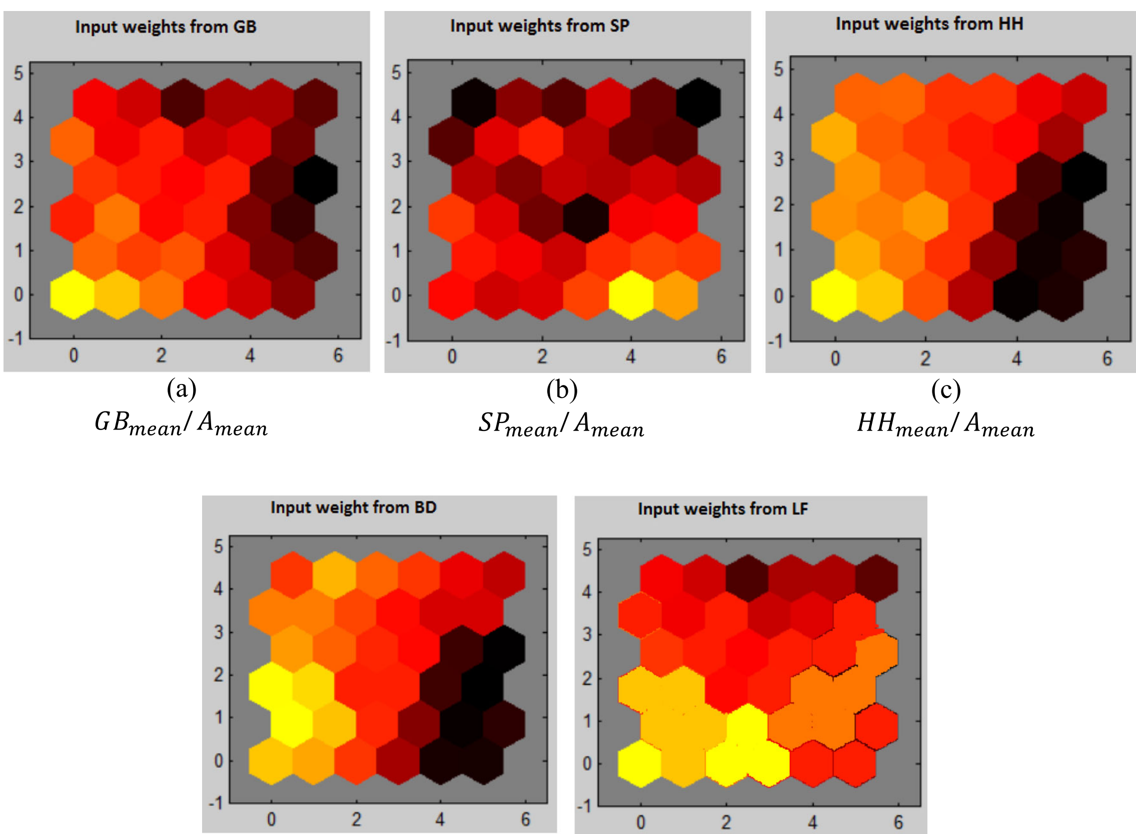
Performance of the SOM in clustering

Mean absolute error (MAE) and *root mean squared error* (RMSE) are the most popular metrics used to measure accuracy and apparently performance of SOM models even though MAE and RMSE are primarily used for continuous variables. The definition of MAE and RMSE is given by the following formulas:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - \overline{x}_i| \text{and } \mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}_i\right)^2}$$

where the quantities x_i and $\overline{x}_i$ correspond to the predicted value of the model and the actual value respectively in relation to the entity x. RMSE has the benefit of more penalizing large errors, and therefore it is used more than MAE. Since we forced the system to produce five classes using the *k-nn* classifier after the initial SOM categorization, we cannot compute the two aforementioned criteria for adopters and non-adopters separately.

For this reason, the average of the two average quantities is used for each one of the answer groups as they have been calculated in Table 3. We denote the average of the two general behavior averages in Table 3 as $\overline{GB}$ and similar notation is used for the rest of the answer groups. Hence, the RMSE and MAE are computed for $\overline{GB}$, $\overline{SP}$, $\overline{HH}$, $\overline{BD}$, and $\overline{LF}$. Results show the values of MAE = 1.987 and RMSE = 5.239. These values are the averages of the above five classes and indicate the misplacements of responders to classes 1 to 5 in Fig. 9b due to their preference in their questionnaire answers. The results of RMSE and MAE are typical in values for soft computing applications that contain fuzzy information.



(a) GB_{mean}/A_{mean} (b) SP_{mean}/A_{mean} (c) HH_{mean}/A_{mean}

(d) BD_{mean}/A_{mean} (e) LF_{mean}/A_{mean}

Fig. 10 Component planes for each of the features from Table 3

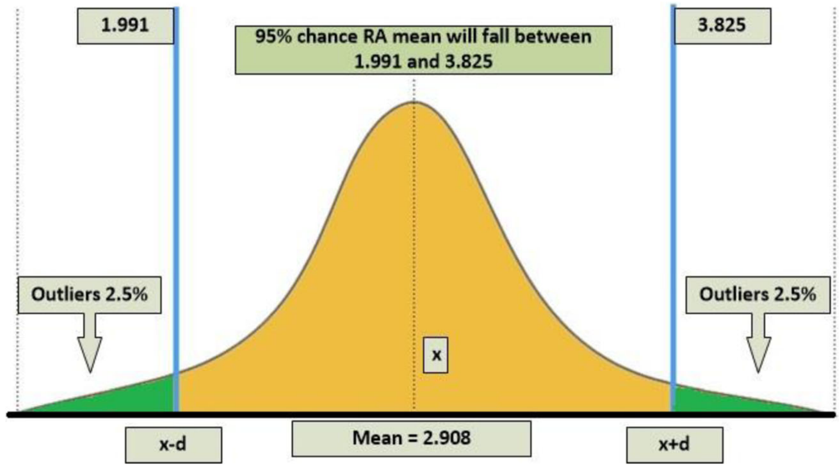


Fig. 11 With probability $q = 0.95$ (yellow shaded area), the number of correct FIS model output lies in an interval $[x-d, x+d]$ around the mean RA score $\bar{x}$

Social determinants affecting recycling

Many variables affect residents' decision-making process of changing attitude towards adopting recycling as every practice. The resident attitudinal survey showed that the three most important questions (the ones that summarized the categories of social issues) have been ordered differently to the residents that are adopters of the recycling practice than the non-adopters. More non-adopters believe that the findings are the most critical and show that the drivers of environmental concern and the social perception of hygiene and health are more influential than the economic status and the lifestyle of the respondents. For this reason, we used these variables as the perception variables. The FL system developed having the previous statistical findings in mind to develop the rule set for inference. The "Performance of the FIS models" subsection proves how close the inference system can perform to achieve similar findings as the statistical ones proving the statistical significance of our test in the range of 0.01. On the other hand, the use of SOM neural networks uncovered the profile of the five categories of questions of social issues involved according to the survey.

One important caveat in the study is that the data is biased. When a resident is asked questions relating to a social issue, everybody tries to present better behavior even though this is not always the case. Thus, to validate the model and provide policy direction, a larger sample is required for further survey study.

Conclusions

The evaluation and establishment of social determinants that affect specific public attitudes such as recycling behavior are difficult tasks, due to the fuzziness in measuring attributes, perceptions, and beliefs of adopters and non-adapters of the methodology. The uncertainty introduced in drawing conclusions from attitudinal surveys by just only calculating statistics makes FL a suitable tool to deal with ambiguous data or data that hide complex parametric associations.

Based on this assumption, we developed a FL system that uses three aggregated fuzzy input variables incorporating the attributes of environmental concern, general behavior, social perception, hygiene, health, economic status, and lifestyle. For this system, we also developed a rule set as a means to de-fuzzify the FL system outcome. In order to experimentally verify the correctness of this system, we also provided the results from statistical methods that estimate the statistical significance as to how close the outcome of the FIS models lies around the true statistics coming from the survey within a confidence interval. Results showed close statistical significance in the range of $p = 0.05$ using Pearson's correlation test and $p = 0.01$ using Kendall's and Spearman's pairwise correlation tests.

We also introduced the application of SOM as a novel approach to segment and cluster public opinion related to recycling by using a variety of clustering parameters. What has proved to work closely to the real statistical output (RMSE = 5.239) was the creation of a spatial model based on characteristics to be the ratios of answer groups to the overall answer mean using the Likert scale.

Future challenges

The novelty suggested in this paper is due to the fact that established social science methods and a set of artificial intelligence methodologies (instead of pure statistical or numerical methodologies) are incorporated in solid waste management practices, thus providing adequate results. However, there are some other challenges that such systems must overcome: (a) mostly the combination of the fuzzy logic system and the SOM system should be refined to be able to predict the correct attitude of a future resident in relation to recycling behavior, taken into account specific characteristics of his/her social perception; (b) the system must be further rectified to discover and highlight the higher importance of specific behavioral characteristics as opposed to others, as at this point all attitudes from all answer groups equally participate in the findings of corresponding averages; and (c) since waste treatment and recycling provide a measure of sustainability, it will be useful to make a specific study to analyze and gain deeper knowledge relative to the percentage of this affect as opposed to the overall impact towards the recycling behavior (in other words to prove the significance of the social affect in relation to the other type of impact towards recycling). This study has explored the applicability of soft computing model to social acceptance issues and discussed potential policy implications. To make concrete policy suggestions, more work is needed in the future, both with regard to data (larger sample) and methodology (more delicate models).

Appendix

Table 5 Pair correlations between the SURVEY statistics and the FIS model statistics

Correlations

		SURVEY	FIS
SURVEY	Pearson Correlation	1	,851*
	Sig. (2-tailed)		,032
	N	6	6
FIS	Pearson Correlation	,851*	1
	Sig. (2-tailed)	,032	
	N	6	6

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

			SURVEY	FIS
Kendall's tau_b	SURVEY	Correlation Coefficient	1,000	,867*
		Sig. (2-tailed)	.	,015
		N	6	6
	FIS	Correlation Coefficient	,867*	1,000
		Sig. (2-tailed)	,015	.
		N	6	6
Spearman's rho	SURVEY	Correlation Coefficient	1,000	,943**
		Sig. (2-tailed)	.	,005
		N	6	6
	FIS	Correlation Coefficient	,943**	1,000
		Sig. (2-tailed)	,005	.
		N	6	6

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 Pairwise sample Statistics

Paired Samples Statistics

			Statistic	Bootstrap[a]			
				Bias	Std. Error	97% Confidence Interval Lower	97% Confidence Interval Upper
Pair 1	SURVEY	Mean	2,71483	,00190	,13734	2,37417	2,97969
		N	314				
		Std. Deviation	,365718	-,045645	,098090	,099728	,492955
		Std. Error Mean	,149304				
	FIS	Mean	2,92467	,00242	,11540	2,66579	3,17461
		N	314				
		Std. Deviation	,306565	-,033548	,068177	,100830	,403236
		Std. Error Mean	,125154				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Paired Samples Correlations

		N	Correlation	Sig.	Bootstrap for Correlation[a]			
					Bias	Std. Error	97% Confidence Interval Lower	97% Confidence Interval Upper
Pair 1	SURVEY & FIS	314	,851	,032	,042	,136	,552	1,000

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	97% Confidence Interval of the Difference Lower	97% Confidence Interval of the Difference Upper			
Pair 1	SURVEY - FIS	-,209833	,191979	,078375	-,445183	,025517	-2,677	5	,044

Bootstrap for Paired Samples Test

		Mean	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	97% Confidence Interval Lower	97% Confidence Interval Upper
Pair 1	SURVEY - FIS	-,209833	-,000522	,069556	,077	-,382000	-,085374

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

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