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Using fuzzy logic and neural networks to classify socially responsible organisations

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Academics and practitioners have not yet developed an adequate method to evaluate the social performance of organisations that includes a robust and comprehensive approach of sustainability and uses the most relevant data sources. However, sustainability rating agencies are evaluating the social performance of organisations according to their own methodologies, which are not always clearly explained to stakeholders; and the evaluations they provide are being used as a reference in markets. This study contributes to research on the evaluation of social performance in organisations, by means of an innovative methodology that combines the use of neural networks and fuzzy logic for the development of expert systems suitable for classifying organisations according to their performance on Corporate Social Responsibility. The methodology has been validated in a simplified scenario and results indicate that it is suitable for replicating the classifications provided by sustainability rating agencies.

Keywords: Corporate Social Responsibility (CSR), neural networks, fuzzy logic, performance measurement, sustainability rating agencies

1. Introduction

The concept of sustainable development defined in the Brundtland Report (WCED, 1987) is built on three basic pillars: economic prosperity, social equity and environmental protection. However, there is no single concept of sustainability and for that reason, there is no commonly accepted method of measuring it (McWilliams *et al*. 2006, Lopez *et al*. 2007). Sustainable development is undoubtedly a complex notion open to numerous interpretations (Atkinson 2000). Therefore, it is sometimes difficult to estimate the corporate performance in Corporate Social Responsibility (CSR) terms (Graafland *et al*. 2004), take business decisions and make comparisons among companies because of the numerous, and differing, performance measurements (Krajnc and Glavič 2005) and the quality of available information (Belu 2009), particularly when no consensus has yet been reached on the evaluation methodology (McWilliams *et al*. 2006).

Achieving progress in systems of CSR performance evaluation is needed for two reasons: (a) to improve the procedures used internally for reviewing the effectiveness

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and efficiency of strategies implemented to promote CSR; (b) to provide the various stakeholders with better mechanisms for assessing CSR compliance and sustainable development. According to Schuler and Cording (2006), stakeholders consider that the information provided by external sources, regarding the performance of a company, has a greater impact on their decisions than information provided by the company itself.

Currently, various types of regularly provided information are used to evaluate CSR performance. In addition to annual financial reports, there are specific CSR or sustainability reports which may include indicators of environmental, social and economic performance, as well as a discussion about corporate governance. They are supported by proposals such as the UN Global Compact or the guide for the preparation of sustainability reports delivered by the Global Reporting Initiative (GRI). However, the many and varied indicators used in sustainability reports do not offer an overview of CSR performance, because their approaches are basically segmented. Accordingly, the elements of corporate governance, environmental, economic, human rights, labour rights and social action are assessed separately.

Moreover, it is not surprising to find, in the literature, different methods used to quantify the performance of CSR, such as: (a) content analysis; (b) measurements of personal perceptions through interviews, surveys and questionnaires; (c) indices of reputation; (d) various one-dimensional indicators; (e) case studies (Waddock and Graves 1997, Maignan and Ferrell 2000, Igalens and Gond 2003, 2005, Soana 2009, Turker 2009, León *et al.* 2010) and (f) ratings or indices developed by experts or specialised companies, following different methodologies, and sometimes with final integrated rates (Moneva *et al.* 2007, Muñoz *et al.* 2008, Rivera and Muñoz 2010).

The ranking of firms according to their sustainable performance has become relevant. As a result, the number of agencies or associations that provide ratings of corporate social responsibility has increased rapidly (Epstein and Manzoni 2006). According to Belu (2009), corporate membership in CSR rankings (among others) are treated as proxies for CSR practice. However, agencies reveal little when explaining the evaluation criteria used, particularly those related to risk management. As a result, the direct analysis of this information by investors is difficult; and companies are faced with a lack of information that makes it difficult for them to discover which actions they have to do in order to enter in a sustainability index (Escrig *et al.* 2010).

In this context, this work advances the construction of methodologies for analysing and measuring overall CSR performance. Its main objective is to propose a methodology which replicates evaluation models of sustainability rating agencies. The uniqueness lies in the use of neural networks and fuzzy logic for working with complex datasets that are of limited use in the field of social performance measurement. These models are relevant for the generation of information on the social, environmental, economic and governmental aspects which will contribute positively to the formation of opinions and decision making by stakeholders, as well as enabling better monitoring and strategic management by those organisations committed to sustainability. The development of these models will help to increase our understanding in the field of socio-economic evaluation.

This paper is divided into seven sections. The introduction is followed by a brief analysis of sustainability rating agencies and a brief explanation of measuring sustainability through fuzzy logic and neural networks. The fourth section presents the proposed methodology for classifying organisations according to their social responsibility performance, and section five presents a study design. After the presentation of the results obtained, the main conclusions are provided in the final section.

2. Sustainability rating agencies

To ensure that a firm is socially responsible it is essential to be able to express the principles of CSR in measurable variables. The analysis of social responsibility is at an early stage. However, sustainability rating agencies study businesses and make evaluations in social, environmental and corporate governance terms. They are the link between stakeholders and companies (Schäfer 2005). The growth of socially responsible financial markets, and the fact that investors are demanding more information, are contributing considerably to the increasing relevance of rating agencies.

Despite the increasing number of environmental, social and governance (ESG) rating agencies, i.e. sustainability rating agencies, there is no standard methodology for the evaluation of firms.

Ducey and Larson (1999) noted that measuring sustainability has a number of limitations associated primarily with the scarcity and quality of available information. Another relevant issue refers to the difficulty of defining the border between sustainability and non-sustainability when using an abstract concept, or a wide range of indicators that are difficult to summarise in a single measurement (Phillis and Andriantiatsaholiniaina 2001).

The complexity in the development of synthetic sustainability indices makes it difficult to design evaluation methodologies. Literature provides some examples of the construction of fairly global indicators. Nevertheless, these are usually built from initial variables with basic procedures, and frequently the aggregation does not reach the final step – with the main aspects being kept separate. Examples can be found in specialist rating companies that usually make comparisons against industry averages (Igalens and Gond 2003, 2005). Progress is needed in this respect (Epstein 2008); and there are calls in the academic world for the establishment of a standard assessment methodology for use by ESG rating agencies (Krajnc and Glavič 2005, Waddock 2008, Escrig *et al*. 2010).

Most sustainability ratings agencies quantify the sustainability of firms by aggregating scores of the different criteria for evaluation used by them. Other agencies give differing weightings to their analysis criteria. However, all these methodologies are not publicly available and therefore companies not evaluated by the agencies are not able to know their potential position according to the sustainability criteria considered by agencies. Furthermore, the different criteria, evaluation and scoring systems used by the sustainability rating agencies make it difficult for companies to predict what position they would achieve in each rating. As a result, it would be interesting for companies to have tools for evaluating their sustainability at their disposal.

3. Measuring sustainability through fuzzy logic and neural networks

Various methodologies integrating expert knowledge offer great potential for measuring complex organisational results which have been traditionally valued qualitatively. In this sense, the design of expert systems using fuzzy logic is being widely applied as a method of analysis in areas such as business organisation and financial economics (Shapiro 2004, Diaz and Morillas 2004, Cassia *et al.* 2005, Sheen 2005, Tiryaki and Ahlatcioglu 2005, Bottani and Rizzi 2006, Gunasekaran *et al.* 2006, Lin *et al.* 2007, Perez Gladish *et al.* 2007, Wu and Lee 2007) and this reflects the usefulness of the mathematics of uncertainty in an environment characterised by profound changes in business activities (Gil Aluja 1996).

Based on this and previous work in measuring risk and sustainability by Phillis and Andriantiatsaholiniaina (2001), Muñoz *et al.* (2008), Phillis and Davis (2009) and Rivera and Muñoz (2010), it is proposed to transfer these methodologies to the generation of models that provide information regarding the positioning of an organisation in terms of sustainability. This information will have multiple uses – being intended for internal management and external stakeholders (investors, government, society, etc.).

In this context, and following Phillis and Andriantiatsaholiniaina (2001), fuzzy logic (Zadeh 1965) is offered as an appropriate tool for evaluating sustainability, not only in macroeconomic terms, as aforementioned works show, but also in relation to the organisations' approach to sustainable development, that is, in relation to the CSR, for several reasons: (a) it enables the handling of complex concepts and polymorphisms that are difficult to quantify, given that they incorporate linguistic variables; (b) it is a mathematical tool that enables simulation of the dynamics of a system, without a detailed mathematical description.

Fuzzy logic is a sort of non-dichotomic logic which tries to quantify the uncertainty frequently related to phenomena. This quantification admits different degrees of truth, whereas dichotomic logic only considers two possibilities: true or false. Based on fuzzy logic theory, it has been developed the fuzzy set theory (Zadeh 1965).

According to Zadeh (1965) a fuzzy set is defined as a 'class' with a continuum of grades of membership. A fuzzy subset A of a universal set is defined by a membership function $fA(x)$ which associates each element into a real number in the interval *(0, 1)*. The fuzzy inference system, known also as 'fuzzy-rule-based system', 'fuzzy expert system' or 'fuzzy model', is a popular methodology for implementing fuzzy logic (Shapiro 2004). Jang (1993) described the five functional blocks that comprise the fuzzy inference system: (1) database which defines the membership functions of the fuzzy sets; (2) rule base, containing fuzzy if–then rules; (3) decision-making unit or inference engine (Shapiro 2004); (4) fuzzification interface; and (5) defuzzification interface.

A neural network is a powerful technique inspired by the way the biological nervous system processes information. This technique consists of a large number of interconnected elements (neurones) working at the same time through a set of algorithms. Thus, neural networks can solve real problems if these can be mathematically represented.

Neural networks have the ability to learn from experience, adapting their behaviour according to a specific environment in order to improve their performance. To that end, neural networks need to be trained to approximate an unknown function or process, based on available input and output data. In this regard, one of the most common procedures to train neural network classifiers is the back-propagation (Rumelhart *et al.* 1986), which is based on an optimisation problem that looks for a set of network parameters, specifically weights, with the end result of obtaining the best classification performance (Mazurowski *et al.* 2008). The back-propagation algorithm is a standard learning algorithm of the Fed-forward Networks (Haykin 1999).

Neural networks have been used in a variety of applications, which can be grouped in four fundamental categories: clustering, classification, function approximation and prediction. A neural network can group input data, representing objects or individuals, into sets that are similar to each other. Moreover, it can be used to assign each object, or individual, to a specific class. With regard to function approximation, neural networks, from input vectors, construct a function that generates approximately the outputs of the unknown process that is expected to model.

A significant group of researchers (Vellido *et al.* 1999, Malhotra and Malhotra 2003) have argued that neural networks can be a more appropriate tool than traditional statistical tools, because: (a) the underlying functions controlling business data are generally unknown and neural networks do not require a prior specification function, only a sample of input-output data to learn and train the process; (b) neural networks are flexible – the brain adapts to new circumstances and can identify non-linear trends by learning from the data; (c) neural networks can work with fuzzy data (very common in economics); and (d) they are able to deal with incomplete information or noisy data and can be very effective, especially in situations where it is not possible to define the rules or steps that lead to the solution of a problem. In this regard, a significant number of empirical research studies have compared neural network methodology with econometric techniques for modelling ratings, and consistent with theoretical arguments, the results clearly demonstrate that neural networks represent a superior methodology for calibrating and predicting ratings relative to linear regression analysis, multivariate discriminant analysis and logistic regression (e.g. Surkan and Singleton 1990, Kim *et al.* 1993, Daniels and Kamp 1999, Bennell *et al.* 2006).

Academics are increasingly exploring neural networks methodology as a new tool for modelling decision processes and prediction in the area of finance, such as corporate financial distress and bankruptcy (Ahn *et al.* 2000, Lee *et al.* 1996), loan evaluation and credit scoring (Baesens *et al.* 2003, Malhotra and Malhotra 2003), and bond rating (Chaveesuk *et al.* 1999, Bennell *et al.* 2006). However, we do not find evidence of neural networks applied to sustainability rating agencies. Therefore, given that neural networks have been used for replicating unknown processes with complex relationships among variables and imperfect data, we consider neural networks are an appropriate methodology to model the behaviour of sustainability rating agencies.

4. Methodology

In spite of numerous surveys of neural networks applied in business, and the fine properties of this powerful technique, we have not been able to find works that use neural networks to evaluate social performance.

This section describes the methodology designed by SoGReS group for the classification of companies according to their CSR, and is based on expert knowledge. The methodology combines the use of neural networks and fuzzy logic, and proposes some steps particularly designed to integrate expert knowledge in a computerised expert system for the classification of organisations according to some key indicators.

The methodology is structured according to a well-defined set of phases that includes the use of specific mathematical tools. During those phases, the methodology provides guidelines for the definition of a key CSR indicators repository, the compilation of information for the expert system training and the implementation and evaluation of the expert system.

The methodology is structured according to the phases in the following sections.

4.1. Sustainability key indicators selection

During the first phase, an exhaustive analysis of various economic, social and environmental indicators, as well as indicators of corporate governance (as defined by existing CSR information generating tools), is performed in order to make an objectification and quantification of their applicability for generating sustainability indices that can be used by organisations and stakeholders. The indicators should be selected according to the information that the rating agencies declare they use in assessing sustainability performance, in order to minimise the differences among criteria used by the agencies and the system to be developed. The more similar the indicators used by rating agencies and the neural network the more accurate the output results. Nonetheless, in the case of replicating ratings where inputs are not public, it should be desirable to introduce a large number of variables that influence the output. In this regard, the neural network is expected to minimise or nullify the weights of those indicators that do not provide relevant information to mimic the rating agencies scores.

The Global Reporting Initiative is also a good source of information, since its guidelines for the development of sustainability reports are widely accepted in the business world and it is used in other research for appraising organisations' sustainability. Many organisations have already implemented the indicators specified in the GRI into their management systems.

The ultimate goal is to make a set of indicators that cover the possible variables to be used as input values for the neural network. As a result of this phase, a complete specification of indicators covering social, environmental and economic results of organisations should be designed.

4.2. Expert knowledge harvesting

The use of neural networks for the purpose addressed in this paper requires providing the neural networks with the knowledge to be replicated. In this case, the knowledge used is the information provided by sustainability rating agencies.

During this phase, it is necessary to collect as much information as possible that is available about the ratings to be simulated. That information should include, on the one hand, the data related to indicators used by rating agencies to evaluate the social performance of as wide a sample of companies as possible, which has been explained in the previous phase. On the other hand, the scores are needed for the sample of firms provided by the sustainability rating agency that is being replicated.

All the information should be carefully stored in a well-structured database in order for it to be used efficiently in the following phase, but also to identify possible information deficiencies that could negatively influence the neural network's teaching process and its final performance. Although trained networks can calculate quite precise outputs when they are used with noisy and incomplete inputs, the training process must be as precise as possible in order to grant an optimum learning.

4.3. Definition of inputs and outputs

The main purpose of this phase is to prepare the data collected in the previous phase to be used by neural networks. This involves preparing input variables and defining output variables.

Regarding input variables, it is necessary to proceed in a specific manner depending on the nature of the data, making distinctions among numeric indicators and qualitative indicators.

With respect to numeric indicators, data should be normalised among all the values in the sample. Any normalisation process can be used, for example, the one followed by Krajnc and Glavic (2005) and Muñoz *et al.* (2008).

Qualitative indicators can be classified into descriptive and categorical indicators, both to be translated into numeric indicators. Focusing on descriptive indicators, which use text to define a state or situation, the process to translate them to numeric indicators, and following previous research results (Muñoz and Rivera 2008, Rivera and Muñoz 2010), may be performed using public databases with business information (Bank of Spain results database, National Institute of Statistics, statistics from Ministry of Labour and Social Affairs, etc.) and private databases (SABI, EIRIS) to objectively identify those numerical proxies that best fit the specific indicator. An alternative method of quantifying these indicators is to use standardised surveys related to issues considered by the specific indicator and whose usefulness has already been demonstrated in other fields. The resulting numeric indicator should also be normalised.

Focusing on indicators referring to both categories and properties, they are defined as follows. Each indicator having a value according to a set of categories is defined as a set of input variables for the neural network, one for each category, whose values would be 0 in all cases apart from the one representing the category the organisation belongs to, that will be set to value 1. For the specific case of indicators that have a value in two categories, only one input variable is necessary in order to represent the indicator, so that each binary value represents one of the possible values in the categories' set. In the same way, properties are also defined as binary input variables that will be set to value 0 when the company does not have the property, and 1 otherwise.

Regarding outputs, this methodology has been designed to provide two types of outputs: numerical marks and categorical classification. The same as input variables, it is necessary to normalise numeric values in the first case, and to define as many binary outputs as categories in the second one.

In this phase it also appears that the use of fuzzy logic is a key tool for the preparation of input and output variables. Fuzzy logic may be extremely useful in the process of translating qualitative indicators, categories and properties to numerical values that may considerably enhance the performance of the neural network and simplify its design, reducing the number of input and output variables without losing significant information. In the same way, its use may help to produce qualitative outputs, where separation among categories is not completely clear.

4.4. Neural network selection and training

During this phase, the neural network is developed that will learn the necessary knowledge to replicate the behaviour of the selected ratings. Hornik *et al*. (1989, 1990) demonstrated that multi-layer feed-forward networks are able to accurately approximate a large class of functions, and their derivatives, with a single hidden layer. In addition, Hagan *et al*. (1996) commented that neural networks with sigmoid transfer functions in hidden layers could produce a response to complex functions. Depending on the expected outputs, the appropriate neural network should be used.

In the case of replicating a rating providing numerical marks, where the output of a specific organisation is expected to be a numeric value, the neural network to be used is an N-layered feed-forward network (N > = 2) with an unique output and with sigmoid transfer function in hidden layers and linear or positive linear transfer functions at the output layer (Figure 1). These networks are especially useful in approximating multi-dimensional functions, since they can fit arbitrarily well when consistent and enough input and target data are proved during their training phase.

In the case of replicating a rating providing a classification according to specified categories, the neural network to be used is an N-layered feed-forward network (N > = 2) with as many binary outputs as categories and with sigmoid transfer function in hidden layers and competitive transfer function at the output layer (Figure 2). These networks are especially useful in approximating pattern recognition problems, using well-defined and separated categories and providing consistent and enough input and target data during their training phase.

Once the neural network is constructed, its weights and biases have to be adjusted to produce the appropriate outputs. For such a purpose, a supervised learning process is performed. This learning process requires providing the net with a set of examples of proper network behaviour; that is, a set of examples of organisations, including all considered indicators, and the final score provided by the selected rating agencies.

The learning process would be strongly influenced by the indicators used, the available training set and the ratings considered as target values. During this process, many configurations of the neural network may be necessary until a good approximation is obtained. These parameter configurations may be tested automatically in order to reduce human efforts, so it may be desirable to develop

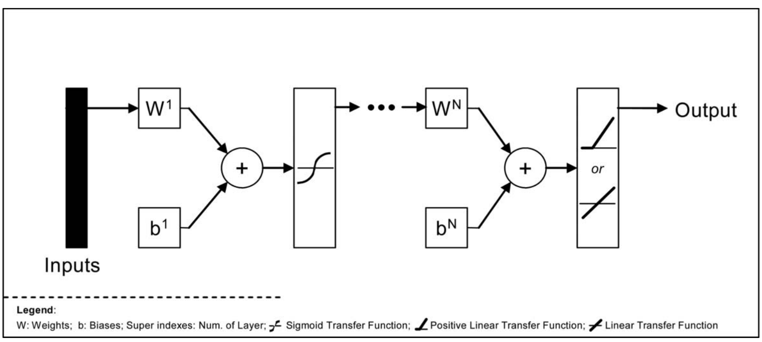

Figure 1. Neural network for replication of ratings providing numerical marks.

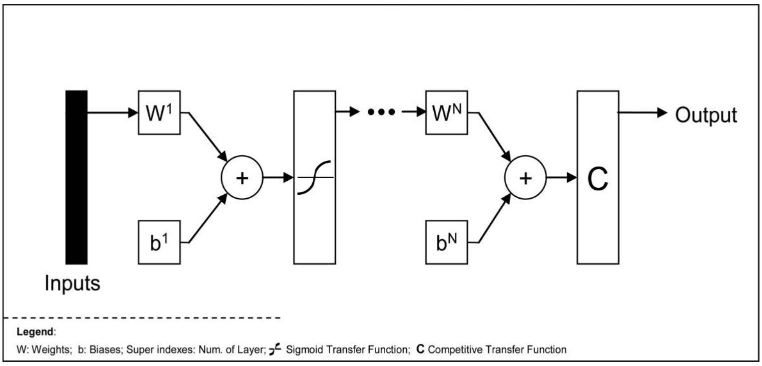

Figure 2. Neural network for replication of ratings providing marks as categories.

a program to automatically train and test the performances of different neural networks, using diverse combinations of the following parameters:

- Number of hidden layers
- Number of neurons per layer
- Size of training datasets
- Training algorithms
- Training algorithms' variables (error, iterations, gradient, etc.).

The proofs should be carried out in the incremental neural network's complexity until significant improvement is not obtained when complexity is increased, trying to keep the resulting neural network as simple and small as possible. The main reason for that purpose is that, given the nature of the problem that is being addressed, the resulting neural network is neither expected to be retrained in the future nor to adapt its behaviour during its use, but it is expected to be used by organisations in order to evaluate their sustainability performance. That requires the network to be widely available; and therefore it has to be efficient and it should require as few computational resources as possible.

As a result of this phase, the most appropriate neural network, defined and trained according to the optimum set of parameters, can be identified by comparing the mean absolute error of the cross-validation testing set offered by each one of the configurations. That net, when offering an acceptable error rate, is expected to be useful for companies not evaluated by the sustainability rating agencies, as long as it can be used by them in order to gain an approximation of the rating they would obtain if they were analysed by the agency.

5. Study design

Due to limitations on access to databases containing information about sustainability performance indicators of organisations, the developed methodology has been empirically applied in a simulated scenario, in order to test its applicability. For such a purpose, two rating processes have been simulated. The set of indicators and outputs used in these processes have been defined according to the sustainability rating system proposed by Moneva *et al.* (2007) and Muñoz *et al.* (2008). This rating follows the triple bottom line concept (economic, social and environmental) through the integration of the stakeholder business orientation, the disclosure level of sustainability and its economic results. The whole process has been carried out as follows.

First, a set of key indicators was chosen. Table 1 shows the indicators used, which refer to corporate strategic consistency in terms of commitment and social performance (Stakeholder Orientation and Sustainability Reporting) and the results obtained of the company's economic-financial performance (Return on Total Assets and Return on Shareholders' Funds). It should be noted that these indicators will be used as inputs for both systems designed to simulate sustainability rating processes, but also as input variables for the neural networks.

Once the indicators were chosen, two processes of rating systems were designed, which came from two different approaches: (1) fuzzy logic methodology, using fuzzy inference system including logical high-level rules; and (2) mathematical aggregations based on experts' criteria. Both ratings were designed to produce a numeric output as an aggregation of the input values. The rating systems for the simulation were designed as follows:

Fuzzy logic system. The fuzzy rating system was designed using fuzzy inference system (FIS) proposed by Muñoz *et al*. (2008). As Jang (1993) stated, five functional blocks form the FIS. Numeric variables are the system inputs. These crisp variables are transformed, through a fuzzification process, into grades of membership for linguistic terms of fuzzy sets, with the help of previously defined membership functions. The resulting linguistic variables become the fuzzy inputs for the inference engine.

Figure 3 shows the generation of the sustainability rating based on fuzzy logic inference proposed by Muñoz *et al*. (2008). First, organisations have been classified as shareholder orientation or stakeholder orientation, according to the analysis of the corporate mission and values (Stakeholder Orientation Index, SOI); and 'opaque', 'pro-translucid', 'translucid', 'pro-transparent' or 'transparent', according to the characteristics of the information provided to stakeholder (Sustainability

Table 1. Indicators.

Indicator	Definition
Stakeholder orientation	The stakeholder strategic approach declared in the company's principles and corporate values (the corporate mission)
Sustainability reporting	Parameters: (1) if the organisation has sustainability information at public disposal; (2) it can be qualified as a report; (3) level of compatibility to generally accepted guidelines – Global Reporting Initiative 2002 Guide (GRI 2002); (4) quality of the provided information – the GRI qualification 'in accordance'; and (5) the validation and verification or certification reports
Return on total assets	Economic profitability
Return on shareholders' funds	Financial profitability

Sources: Moneva *et al*. (2007); Muñoz *et al*. (2008).

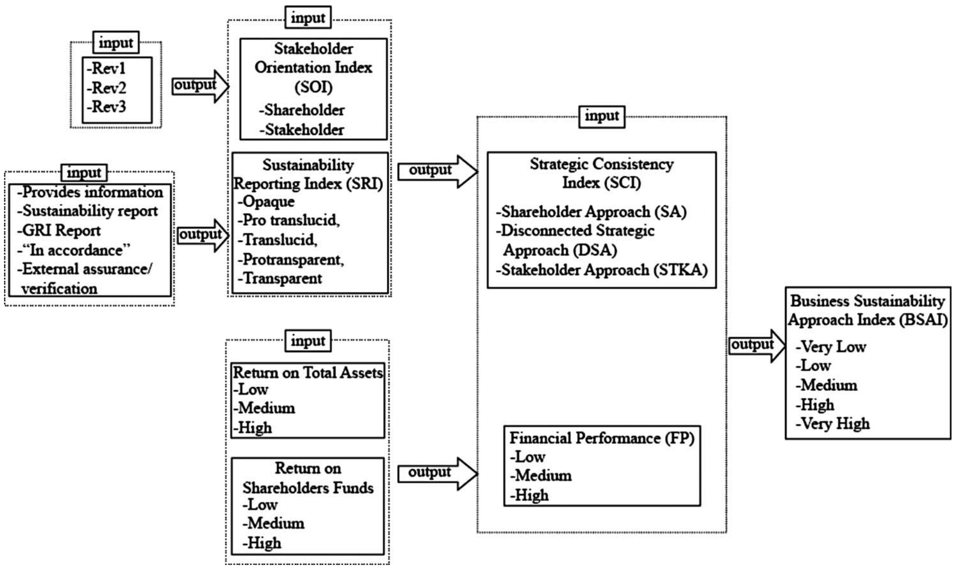

Figure 3 Business sustainability approach rating generation.
Source: Muñoz *et al*. (2008).

Reporting Index, SRI). Both indexes (SOI and SRI) comprise the inputs for the fuzzy inference system for generating the Strategic Consistency Index (SCI) of the organisation, as an answer to the expectations and needs of a number of stakeholders. This index (SCI) measures the strategic consistency in their stakeholder management, based on management orientation and commitment towards the shareholders or the stakeholder. In addition, Financial Performance Index (FP) contains normalised financial and economic returns ratios. Finally, SCI and FP make up the inputs for the last fuzzy inference system, whose final outcome is the Business Sustainability Approach Index.

In terms of methodology, following the application of IF-THEN rules, which can be observed in detail in Muñoz *et al*. (2008), a fuzzy output is obtained and expressed in linguistic terms. A fuzzy output is transformed into numeric values using a defuzzification process. The FIS applied in a rating simulator was the Mandany type, using min-operator for the logical AND the max-operator as an aggregation method and the centroid as a defuzzification method. The defined membership function for all cases was triangular membership function.

Mathematical criteria. A large group of sustainability rating agencies use a methodology based on the evaluation of a set of categories (e.g. Oekom research, SAM and Vigeo). Each category can be divided into sub-categories, and these are evaluated using a numeric or linguistic scale. The agency establishes a weight associated with each category and a final score is obtained adding the weighted score for each category. Following this process, we have created a rating system which includes two categories: social performance and economic-financial performance. The first category includes two sub-categories (management orientation and transparency) and they are evaluated depending on whether the company follows a shareholder or stakeholder approach and the level of transparency in sustainability provisions, using a numerical scale. On the other hand, the second category consists of the average of an economic and financial ratio. We obtain a final score by means of simple mathematical criteria; specifically, we carry out a weighted sum of the categories, taking into account any possible incoherence between the management orientation and the behaviour of the company. The final score is calculated according to the equation:

$$BSAI = SO \cdot W_{So} + \frac{SR \cdot W_{SR}}{5} - \left(SO \cdot W_{So} - \frac{SR \cdot W_{SR}}{5}\right)^2 + RTA \cdot W_{RTA} + RSF \cdot W_{RSF} - (RTA \cdot W_{RTA} + RSF \cdot W_{RSF})^2 \quad (1)$$

where:

SO = Stakeholder orientation (values 0 or 1)
W_{So} = Weight for stakeholder orientation
SR = Sustainability report (values 0 to 5)
W_{SR} = Weight for sustainability report
RTA = Return on total assets (values 0 to 1)
W_{RTA} = Weight for reterun on total assets
RSF = Return on shareholders' funds (valuess 0 to 1)
W_{RSF} = Weight for return on shareholders' funds

A dataset of indicators of simulated firms were randomly generated. To this end, a script based on the Monte Carlo method was developed and fixed probabilities were assigned to the possible values of each one of the input indicators. Other scripts were also programmed for translating the indicators' values to the appropriate input formats for both simulated rating processes.

A simulation was then performed, with both systems using the previously generated input datasets. As a result, two output datasets were generated which represented the scores obtained by each of the simulated companies according to both agencies. In total 80% of the cases of the output were randomly selected to be used as expert knowledge to train the neural networks. Given the numeric nature of the output values, the applied neural networks were N-layered feed-forward with unique output and with sigmoid transfer function in hidden layers and positive linear transfer functions at the output layer.

The previously simulated indicators were also prepared so they could be used as input variables for the neural networks, according to the methodology, by means of a script. Those input datasets, and the previous output datasets, were used to train different neural networks for each of the simulated agencies, varying some of the parameters and contrasting the output of the neural networks with the output of the simulated rating systems, in order to evaluate their accuracy in terms of the linear correlation coefficients, which provided an indicator of a model's overall performance.

6. Results

A program was designed to train 2-layered networks with different numbers of inputs and numbers of neurons. For each configuration, 100 networks were trained and evaluated in order to reduce the influence of the randomly generated training sets. To this end, the training dataset was randomly classified in two sets.

The first set, containing 80% of the cases, was used to train the networks with the back-propagation algorithm, since it is the standard learning algorithm of the Fed-forward Networks (Haykin 1999). In particular, the Levenburg-Marquardt method was used in the simulations. This method shows the most efficient convergence during the back-propagation training process, because it acts as a compromise between the first-order optimisation method (steepest-descent method), with stable but slow convergence, and the second-order optimisation method (Gauss-Newton method) with opposite characteristics (Hagan and Menhaj 1994).

The second set, including 20% of the cases, was used to validate the network generalisation and to stop the training process before overfitting.

Finally, the accuracy of trained neural networks was evaluated. To this end, we calculated the mean of correlation coefficients between the simulated agencies' outputs and the outputs provided by the different network configurations.

Tables 2 and 3 show the average correlation coefficients obtained by the different configurations of the neural networks trained to approximate the fuzzy rating agency (Table 2) and the mathematical criteria rating agency (Table 3).

Although the configuration of other parameters should also be evaluated, in order to determine whether or not there are better approximations, as Tables 2 and 3 show, the developed networks can replicate considerably well the behaviour of the simulated rating agencies.

Table 2. Correlation coefficients obtained for the rating agency with fuzzy logic.

	Number of neurons in layer 1			
Training set size	5	10	20	50
20	0.8574	0.9090	0.9075	0.9202
50	0.8375	0.8685	0.8646	0.8524
100	0.9101	0.9474	0.9456	0.9509
200	0.9446	0.9332	0.9339	0.9242
500	0.9883	0.9233	0.9208	0.9166
1000	0.9909	0.9653	0.9644	0.9647
2000	0.9903	0.9760	0.9797	0.9769

Table 3. Correlation coefficients obtained for the rating agency with mathematical criteria.

	Number of neurons in layer 1			
Training set size	5	10	20	50
20	0.8146	0.6232	0.4047	0.4435
50	0.9545	0.9026	0.7043	0.6851
100	0.9732	0.9719	0.9112	0.9228
200	0.9749	0.9784	0.9722	0.9722
500	0.9774	0.9755	0.9778	0.9779
1000	0.9787	0.9684	0.9800	0.9802
2000	0.9786	0.9772	0.9795	0.9794

Results indicate that the developed methodology may be successfully used to replicate the behaviour of sustainability rating agencies regarding their procedures to evaluate organisations according to their contribution to sustainable development.

The methodology has been applied in a simulated scenario. The aim of future research will be to replicate real sustainability rating agencies, by using real information about organisations, and to test their approximation levels.

7. Conclusions

In the absence of a generally accepted method to evaluate the sustainability performance of organisations, the evaluations provided by sustainability rating agencies are being used as the main reference in the market. Those evaluations are not always clearly explained to stakeholders, and the criteria they use in their evaluations differ between them.

In this paper, a methodology for replicating the sustainability evaluation models used by rating agencies is presented. The methodology integrates the use of neural networks and fuzzy logic in a well-defined procedure. The methodology has not been evaluated with real cases, but the performed simulations show that, using the methodology, suitable neural networks can be developed.

It is expected that the developed methodology will be used by organisations in order to evaluate their sustainability performance according to sustainability rating agencies' criteria.

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