Environmental Responsibility Assessment Using Uncertainty

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Abstract This book chapter is an extension of [34, 35] and adaptation from [36]. This chapter proposes the use of belief-rule based inference engine for Environmental Responsibility Assessment in small and medium-sized enterprises. Such a context-adapted approach is believed to generate well balanced, sensible and Green ICT readiness adapted results, to help enterprises focus on making improvement on more sustainable business operations.

1 Introduction

Turning sustainable development into action and taking control over consequences of not doing so became a central issue of 21st century. A large body of data concerning environmental problems is claiming to be results of unsustainable consumption practices of industrialized world in a large scale [1, 2]. In recent years, organizations have become increasingly interested in commitment to environmental issues. Environment is one of the pillars of the sustainability triangle [3], along with economic and social dimensions. The definition of Environmental Responsibility can be defined as the obligation that a company has to operate in way that protects the environment. This research is focused on assessing the environmental responsibility level of an organization.

Large companies are usually legally bound to prevent their activities from contributing to water discharge, CO_2 emissions to the atmosphere, waste management and soil and noise contamination [4]. ICT is believed to have a great potential in solving these problems. In Sobotta's book [2], many experts debate on how ICTs can support an organization in reducing CO_2 emissions, saving energy and optimizing resource utilization - thus becoming greener and developing towards a more environmental friendly society.

Due to legislation pressure and increase of community awareness, a variety of environmental management systems, standards and tools are being developed and used in order to assist companies to become more environmental friendly. Each of them has its own particular benefits and advantages, but there is no indication of which of them is better for the company's current state. The primary focus of an enterprise's environmental management depends on which industrial sector it is in.

Companies might take a proactive approach to implementing environmental practices based on specific ISO standards relevant to their industry in order to reduce the environmental impact of their activities. Nevertheless, this research concentrates on a more generic and aggregated perspective of defining the environmental responsibility of a company.

Environmental Responsibility level is a very abstract concept and measuring it in an absolute manner is not feasible. Attitude surveys provide many kinds of useful information and environmentally friendly behavior has often been studied successfully, but neither method truly reveals much about environmental performance assessment in organizations [5].

1.1 SMEs and sustainability

Small, micro and medium-sized enterprises make up more than 90% of estimated total number of business sector bodies in the EU [6] and could contribute up to 70% of all industrial pollution [7]. Mostly, large enterprises and corporations are legally bound to incorporate CSR policies, follow internationally recognized environmental standards to secure sustainability in their operations. A compelling amount of research has been conducted and voluntary industry initiatives evolved, such as Eco-Management and Audit Scheme (EMAS), Environmental Management System (EMS), ISO 14001 standard, as means to develop systematic approaches in improving environmental performances of enterprises. Hence, smaller enterprises are usually exempted from those standards due to lack of financial, human resources and time. The research in the field of EMS systems adoption among SMEs has revealed other obstacles such as low awareness, absence of pressure from customers, poor information quality from advisors and skepticism in benefits gaining [8]. That emphasizes the need to provide small and medium-sized enterprises with an easy to access and comprehend, attractive financial savings mechanisms to reduce their footprint and optimize operations in a sustainable way [8–10].

How to measure the Environmental Responsibility level of SMEs? Which is the recommending path that companies should follow towards environmental performance excellence? This research addresses these questions. Therefore, the research aim primarily focuses on the development of a novel assessment and decision support model to help companies evaluate their current state followed by recommendations of behavioural and operational best practices to enhance their environmental responsibility level. This paper demonstrates the feasibility of the Belief Rule-Based (BRB) approach in the assessment of enterprise's level commitment to environmental issues.

In order to address the research aims stated above the research work has been implemented according to the steps described in the Figure below:

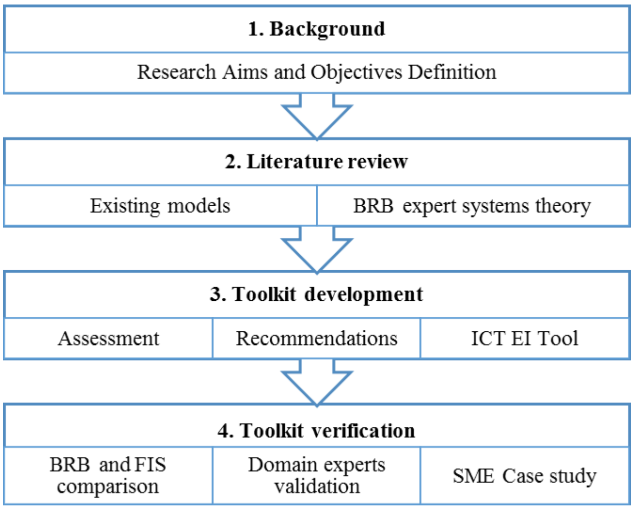

Fig. 1. Research plan

The work commenced with relevant background work and literature review for the problem statement and the BRB expert systems theory has been chosen for the ER Assessment methodology. After the Toolkit development, the BRB model has been compared and validated with Fuzzy Inference Systems theory [11]; verified by domain experts and a case study with a selected SME has been conducted (outside the scope of this chapter but details could be found in [36]).

The remaining of the paper is structured as follows. Section two presents the existing corporate environmental impact assessment models. Section three provides an overview the theoretical basis of Belief Rule-Based methodology applied in research. BRB inference validation and performances comparison with a Fuzzy Inference Systems (FIS) theory are then presented in Section four. A final section concludes the paper with findings, limitations of this research, as well as potential avenues for future research.

2 Literature review

2.1 Existing Environmental Assessment Models

Various evaluation approaches and models for the assessment of companies' environmental impact have evolved. Some of most well-known are SURF Green ICT Maturity Model [12], Sustainability Maturity Model from Industrial Research Institute [13], Sustainability Management Maturity Model of FairRidge Group, Systematic action plan from Fachgruppe Green IT [14], UK HM Government Green ICT Maturity Model [15], Green IT Readiness Framework [16] and SustainaBits Framework and Rating System for Sustainable IT [17] by using which organizations may benefit in raising environmental issues awareness.

Works dedicated to data centres assessment and greening operations have been intentionally excluded from this literature review. Most of the models surveyed are research related models which require minimum knowledge on Green ICT domain and are in formats of scientific works, tables and publications or are abstract and conceptual [16], [17] mitigating the chances to be adopted by non-academic organizations. Some models [12], [13] include an actual assessment by assigning scores per categories, but are not applicable for small and medium-sized enterprises. Most of the models focus on eliminating negative impacts of ICT infrastructure, whereas SMEs need a simple, comprehensive, easy to use and access tool for an assessment of their level of environmental responsibility.

It is evident from literature review that Green ICT and ICT for Greening domain fundamentals in a corporate context need a proper classification and standardization, recognized both by industry and academia. Categorization inconsistencies are demonstrated in models above, and expected to be even more diversified among those which were not identified, skipped or missed. Also, assessment systems do not address qualitative reviews and adaptations towards targeted user groups [14], [15], [16]. Environmental responsibility level assessment is a multidimensional, observational process that requires a more rigorous reasoning approach to handle uncertainties, imprecisions and at the same time, be positive perspective oriented.

Environmentally Responsibility (ER) assessment is characterized by a number of identified factors which are qualitative in nature and can be assessed based on human judgment. Thus, a general ER assessment problem for SMEs could be addressed without a detailed and rigorous audit conducted by affiliated authorities. Such an approach would be able to handle uncertainties, vagueness and fuzziness. Assessment models presented above follow mostly traditional approaches in Green readiness assessment and reasoning, which are incapable of producing accurate ER level results. Expert systems are widely used to deal with knowledge-based decision support systems. Thus, the Belief Rule-Based approach with its ability to infer uncertain knowledge in the domain of Environmentally Responsibility has been applied in this research.

2.2 Belief Rule-Based Expert Systems

Expert system development involves the deployment of an appropriate inference rule engine. Knowledge representation systems are mainly used to support human decision-making and can be transformed into rule-based schemes, which are easy to perceive, understand and deploy [18]. These schemes which express different types of knowledge are usually constructed in the formats of IF-THEN rules, which are widely deployed in the areas of Artificial Intelligence, Decision Support and Expert Systems. Belief Rule-Based Expert Systems consist of two parts: Knowledge Base and Inference Engine, which are used to derive conclusions from rules, either established by experts with domain-specific knowledge, historical data or observation facts provided by users. That is to say, inference engine is a core algorithm of the Belief Rule-Based (BRB) expert system and the following section will examine available reasoning patterns and justify the selection of forward chaining inference based rule engine.

As an alternative to rules engines, one can consider data-driven designs methods, using “lookup tables”, database manipulations where scripts are updated on the fly, or hand-coded IF-THEN-type cases in the application. A primary purpose of a rule engine is the separation of the business and system logic, so that rules can be easily maintained without intervention into the application logic, code recompilation etc. Moreover, rules are stored in an external file and encoded into a human-readable format, ensuring that non-technical experts will be able to collaborate. Logic and data separation is a good OOP pattern, also ensuring loose coupling parameter for Service Oriented Architecture (SOA) based application types. Having a separate file containing all rules support the knowledge centralization aspect, which is even further strengthened by the availability of wide range of Integrated Development Environment (IDE) plugins.

Rule engines have great potential in reducing application maintenance cost, because reasoning makes a clear separation between the logic and data, i.e. separating the application source code (not modified) from the logic code (modified if logic is changed).

An inference engine from the practical view is a piece of software that helps to derive logical conclusions from a set of facts and user observations. There are two types of inference engine logics: forward and backward chaining. Forward chaining (or data driven) is a method that starts with the available information and uses rules to extract more data, as the input data determines which rules are to be used [19]. While in backward chaining (also goal driven) an inference engine would iterate all rules until it finds the one with a consequent, matching the requirement.

2.3 Inference engines

There is a big number of business logic rule engines available in the market, most of which are open source and show impressive performance indicators, but each of which is dedicated to address specific problems. The selection of a suitable engine for this research is based on the following criteria: no cost for a complete version (i.e. open source), Java and IDE integration, extensive documentation and acceptable inference engine performance.

Jess [20] is considered as one the fastest rule engines for Java platform, which offers a direct manipulation and interaction with all Java objects. Lisp-similar description language Jess uses an enhanced version of a Rete pattern matching algorithm. Nevertheless, the last version of Jess 7 has been released in 2007 which makes Jess less likely to meet research needs.

Drools [21] is an open source JBoss and Red Hat Inc. Business Rule Management System (BRMS). It offers several editing and managing tools along with high performance execution. It also provides Eclipse IDE plugin for core development and Drools Flow graphical modelling editor.

OpenRules [22] is another Business Decision Management System (BDMS) that provides a number of tools for rule based decision systems development, which requires less developer support. The main strength of OpenRules is that it allows to import and edit rules in MS Excel, Word or Google Docs formats, which makes it attractive to non-technical domain experts due to ease of its operation. A complete version of OpenRules includes an Eclipse plugin that enables debugging, Web service deployment and integration with any java or .NET applications. Similar to Jess a full version of OpenRules requires a license with a nominal fee. CLIPS [23] is an acronym for C Language Integrated Production System, a software tool for building expert systems. CLIPS itself is written in C language. CLIPS Java API (CLIPS JNI) distribution is also available, but using CLIPS brings an additional overhead with versions support, and IDE integration due to the latest Java version incompatibility.

This is a brief description of selected engines on different measurement criteria, however it should be noted this list is not exhaustive because many other engines have not been discussed in this section. A comparative analysis above reveals that JBoss Drools as an engine that fits all selection criteria and has been chosen to be deployed in this research.

3 Assessment Methodology

3.1 Belief Rule-Based Knowledge Representation and Inference Procedures

Constructed rule-based expert systems based on human knowledge are considered the most visible and fastest growing branch of artificial intelligence (AI) according to Sun's work [24]. There are several common types of knowledge propositions in rule-based systems: Boolean for the concepts which have either true or false values, fuzzy set of propositions for non-clearly defined concepts or an attribute as a variable having a set of possible values it can take. In this research, the possibility of defining Environmental Responsibility in an organization by a list of actions that will lead to more efficient and sustainable performance is proposed. However, it is recommended that the assessment results be accompanied by a more rigorous and continuous audit of the company environmental performance. For the purpose of this research, boolean and fuzzy knowledge proposition sets are used. For example:

"*Prioritization of using eco-labelled equipment will lead to savings on energy consumption*", is more deterministic rather than probabilistic, and it is derived from conclusions established by experts and observation facts provided by statistics.

There are many types of uncertainties in real world decision support systems such as vagueness, imprecision and ambiguity [25], because each knowledge proposition attribute can be described as "high", "medium" and "low" or "true" and "false". The whole concept of ER assessment for a company is a fuzzy, scalable and continuous (i.e could be in a continuous continuum from 0% to 100%) concept, due to infeasibility to obtain precise input data, which will cause inaccuracy in an evaluation process. As it is described earlier, an inference is a reasoning procedure to derive conclusions from a knowledge base. In a forward chaining algorithm, an inference starts iteratively searching for the pattern-match of an input and an if-then clause. When a match is found, it fires the if-then clause followed by triggering an action. However, forward chaining mechanism is not equipped with uncertainty handling. Therefore, decision is made to deploy the forward chaining and elements of belief degrees with a hybrid knowledge representation inference scheme to accommodate uncertainties. For example, in the Hossain's measles diagnosis paper [25], belief distribution is described as follows:

Rk: If (Fever is 'Medium'^ Rash is 'High'^...)

Then measles diagnosis probability is {(High, 0.90), (Medium, 0.10), (Low, 0.00)}, (1)

Proposition in (1) states: belief degree is 90% that the condition is 'high', 10% that it is 'medium', and 0% that it is 'low'. Moreover, input variables involved in inference may not be of the same type. They might be expressed quantitatively and qualitatively and could be different both in type and range. To summarize, there is a need to deploy a hybrid inference schema with Forward Chaining under uncertainty to provide mathematical handling of various input data types and uncertainties handling.

First step in building the knowledge base of a BRB system is to identify relevant antecedent attributes, types of uncertainties and corresponding weights. These then form a generic domain knowledge representation scheme using belief structure. Secondly, a rule base is constructed on the basis of a belief structure, which apprehends nonlinear causal relationships of rules. In a complete belief rule base scheme, input for each antecedent variable is transformed with a set of available referential values. This distribution describes the degree of each antecedent being activated [26].

Suppose N is a set of distinctive referential values for an antecedent attribute $x_i(i = 1 \dots T)$ represented by

$$H(x_i) = \{H_{i,n}, n = 1..N_i\} \tag{2}$$

where $H_{i,n}$ denotes the n_{th} evaluation value for an attribute x_i. Correspondingly, the belief distribution of x_i can be defined as

$$S(x_i) = \{(H_{i,n}, \alpha_{i,n}), n = 1..N_i\} \tag{3}$$

where $\alpha_{i,n}$ is the belief degree to which x_i is assessed to evaluation degree $H_{i,n}$, and $\alpha_{i,n} \geq 0 \; and \; \sum_{n=1}^{N_i} \alpha_{i,n} \leq 1$.

The belief degree is considered to be complete when it is equal to 1 and incomplete when less than 1. Any data type, even without uncertainties can be transformed into evaluation belief distribution [27].

Belief rule-based schema (conjunctive boolean expression) is defined as follows:

$$IF \; x_1 \; is \; A_1^k \wedge x_2 \; is \; A_2^k \wedge \dots \wedge x_{Tk} is A_{Tk}^k,$$
$$THEN \left\{ (D_1, \beta_{1,k}), (D_2, \beta_{2,k}) \dots (D_n, \beta_{n,k}), \right\}$$

$$where \sum_{n=1}^{N} \beta_{n,k} \leq 1 \quad (4)$$

with a rule weight $\theta_k$and attribute weight
$\delta_{1,k}, \delta_{2,k} \dots \delta_{Tk,k}, k \in \{1 \dots L\}$.

Here, $x_1, x_2 \dots x_{1Tk}$ denote the antecedent variables in the k_{th} rule. These attributes belong to the set of antecedent variables $X = \{x_i; i = 1 \dots T\}$ in which each element takes a value from an array of finite sets $A = \{A_1 \dots A_t\}$. The vector $A_i = \{A_{i,n}: n = 1 \dots N_i = |A_i|\}$ is defined as the set of referential attributes for antecedent variable x_i. In the k_{th} rule, A_i^k represents the referential value corresponding to i_{th} antecedent variable. T_k denotes the total number of antecedent attributes in the k_{th} rule; $\beta_{n,k}$is a belief degree to which D_n is assumed to be consequent, taking into account the logical relationship of the k_{th} rule: $Fk{:}\ x_1\ is\ A_1^k \wedge x_2\ is\ A_2^k \wedge \dots \wedge x_{Tk} is A_{Tk}^k$. If $\sum_{n=1}^{N} \beta_{n,k} = 1$ the k_{th} rule is said to be complete and incomplete otherwise. In an exceptional and extreme cases where $\sum_{n=1}^{N} \beta_{n,k} = 0$ it denotes total ignorance on the consequent variable. It should be mentioned that $D = \{D_n; n = 1..N\}$ can act either as a firing action or a concluding statement [28]. For example in case of ER assessment:

R_k: IF the use of ecolabelled equipment is high and switch-off and standby policy is medium and standards compliant strategy is adoption is high},
THEN ER level is {(good, 0.7), (average, 0.2), (fair, 0.1), (poor, 0)}, (5)

where belief distribution representation for ER is considered good with 70% of confidence, 20% for average and 10% sure that ER level is fair. In general it is expressed as:

$$(A_1^*, \varepsilon_1) \wedge (A_2^*, \varepsilon_2) \wedge \dots \wedge (A_T^*, \varepsilon_T) \quad (6)$$

where ε_1 is a degree of belief corresponding to antecedent A_i^* of the i_{th} variable $i = 1 \dots T$ which reflects uncertainty of data and T is the total number of input attributes. And,

$$A(A_i^*, \varepsilon_i) = \{(A_{i,j}, \alpha_{i,j}); j = 1..J_i\}, i = 1..T \quad (7)$$

where $A_{i,j}$ is the i_{th} referential value of the i_{th} attribute and $\alpha_{i,j}$ is a degree to which A_i^* belongs to $A_{i,j}$. The total degree $\alpha_k$with input match of A^k antecedent in the k_{th} rule is calculated by:

$$\alpha_k = \varphi((\delta_{k1}, \alpha_{k1}) \dots (\delta_{kT_k}, \alpha_{Tk}^k)), \quad (8)$$

where φ is an aggregation function for T_k antecedents in k_{th} rule and $\delta_{k_1}(i = 1 \dots Tk)$is the weight of the i_{th} antecedent variable. An aggregation function for subjective probabilities generation is "$\wedge$" operator, i.e $\varphi_{sum}(a, b) = a + b - ab$ [29]. Particularly, the consequent part of a rule is true if only all antecedent variables meet the rule conditions, so the following weighted multiplicative aggregation function is used:

$$\alpha_k = \prod_{i-1}^{T_k} (\alpha_i^k)^{\overline{\delta_{ki}}}$$
$$where\ \overline{\delta_{ki}} = \frac{\delta_{ki}}{max_{i=1\dots Tk}\{\delta_{ki}\}} \tag{9}$$

For the formula above $0 \leq \alpha_k \leq 1, \alpha_k = 1\ if\ \alpha_i^k = 1$ for all $i = 1 \dots T_k$and $\alpha_k \geq 0,\ if\ \alpha_i^k = 0$ for any $i = 1 \dots T_k$ [27].

Also, a consequent value is linearly dependent on an antecedent variable weight, where one attribute may contribute more than another. Unfortunately, in the concept of ER, there is no existing work or justification of assigning different weights for different activities. Thus, in the context of this research, corresponding weights are considered to be equal. Additionally, the inference engine should take into account incompleteness of input data, where antecedent value is not known or partially known. For such cases in this research, inference is being held with worst case scenario for this antecedent, i.e.

$$IF\ 0 \leq \sum_{i=1}^{N} \overline{\beta_{i,k}} \leq 1$$
$$\beta_{i,k} = \frac{\overline{\beta_{i,k}}\left(\sum_{t=1}^{Tk}\left(\tau(t,k)\sum_{j=1}^{Jt}\alpha_{t,j}\right)\right)}{\sum_{t=1}^{Tk}\tau(t,k)} \tag{10}$$
$$where\ \tau(t,k) = \begin{cases} 1, for\ Ut\ in\ Rk\ (t = 1 \dots Tk) \\ 0\ otherwise \end{cases}$$

The formula above saves consequent calculation in cases when not all antecedent variables are involved in a rule inference. Recapitulating again, in an ER calculation all antecedent attributes are included and using worst cases for incomplete input data. If there is any incomplete data, the lowest possible referential value is assumed in order to compute the consequent. Thus, final consequent variable will be generated by combining each consequent for corresponding antecedent. From J. B. Yang's "Rule and utility based evidential reasoning approach for multi-attribute decision analysis under uncertainties" work [30] $m_{j,I(k)}$is the combined probability mass degree of belief in D_j, where:

$$m_{j,k} = \omega_k \beta_{j,k}, j = 1 \dots N$$
$$m_{D,k} = \omega_k (1 - \sum_{j=1}^{N} \beta_{j,k}) \quad (11)$$

Suppose $m_{j,I(K)}$ is the combined belief degree in D_j antecedent-belief degree pair and $m_{D,I(L)}$is the remaining degree. Then, the overall aggregated belief degree $\beta_j\ in\ D_j$ is defined as:

$$\{D_j\}: \beta_j = \frac{m_{j,I(L)}}{1 - m_{D,I(L)}} \quad (12)$$

Thus, the concluding consequent is generated by aggregating L and input data from vector $A^* = \{A^{*k}, k = 1 \dots L\}$ number of rules is represented as:

$$S(A^*) = \{(D_j, \beta_j);\ \ j = 1 \dots N\} \quad (13)$$

Assuming that $u(D_j)$ is the utility of an individual consequent variable (crisp value), single value converted result is equal to:

$$u(S(A^*)) = \sum_{j=1}^{N} u(D_j)\beta_j \quad (14)$$

Lastly, the overall belief degrees are measured by individual antecedent degrees of the k_{th} rule activated by an input which is a building base for the overall output belief degree.

3.1.1 Knowledge base in ER assessment

As previously mentioned, knowledge base in belief rule-based systems is either established by experts with domain-specific knowledge, historical data or observation facts or statistics. In this research, it is based on an in-depth literature review and experts in Green ICT validation:

Here, V_j denotes the category, e.g. V_1 - Equipment procurement compliant with Green ICT guidelines and the optimization of enterprise operations; V_2 - Energy performance improvements and monitoring towards the use of alternative energy resources; V_3 - Energy- aware network engineering adherence; V_4 - Social commitment; V_5 - Waste management. The categories proposed based on the research scope:

1. Dedicated to small and medium-sized enterprises;
2. Only for SME's in-office ICT infrastructure deployment and behavioral best practices in equipment usage;
3. SME's ICT equipment procurement, usage and end-of-life treatment life cycle stages;

Thus, the Knowledge base for the Environmental Responsibility assessment of SMEs is presented in the Table 1 below:

Category	Antecedents
V_1: Equipment procurement compliance with Green ICT guidelines	$A^1_1, A^1_2, A^1_3, A^1_4, A^1_5,$
V_2: Energy performance improvement and monitoring	$A^2_1, A^2_2, A^2_3, A^2_4,$
V_3: Energy aware networks engineering adherence	$A^3_1, A^3_2, A^3_3,$
V_4:Social commitment	$A^4_1, A^4_2, A^4_3, A^4_4,$
V_5:Waste management	A^5_1, A^5_2

Table 1. Categories

Below is a set of a structured questionnaire with categories of items relevant for the assessment of Environmental Responsibility:

V_1:

1. Does your company follow Green ICT procurement guidelines when ICT equipment is purchased?

- ○ Always
- ○ Sometimes
- ○ Never

2. Have you ever used Life Cycle Impact Assessment as a product/service purchase criterion?

- ○ Yes
- ○ No

3. Do you prioritize eco labels (e.g. EPEAT, Energy Star, EU Ecolabel, SWAN etc.)?

- ○ For 100 % of equipment (Excellent)
- ○ For between 70 to 99 % of equipment (Good)
- ○ For between 40 to 69 % of equipment (Fair)
- ○ For less than 40 % of equipment (Poor)

4. Are you familiar with use of services that minimize the energy consumption and environmental impact of ICT equipment (e.g. virtualization, optimization, etc.)?

- ○ Extremely
- ○ Moderately
- ○ None

V_2:

5. Have you ever conducted any ICT equipment energy consumption assessment?

- ○ Yes
- ○ No

6. Is use of switch off and standby modes common in your company?

- ○ Yes for all
- ○ Occasionally
- ○ No

7. Have you installed any power management software in your company ICT equipment?

- ○ Yes
- ○ No

8. Have you followed any systematic approach for energy efficiency improvement (e.g. data collection, and data analysis)?

- ○ Always for all
- ○ Sometimes
- ○ Never

9. Does your company use energy from any of these renewable sources? (e.g. solar, wind, geothermal or biomass energy)?

- ○ Yes, from at least one
- ○ No

V_3:

10. Do the following statement apply to your company? “The network infrastructure makes use of equipment that adheres to the latest energy efficiency standards (sleep mode or Energy Efficient Ethernet).”

- ○ Extremely
- ○ Moderately
- ○ Not at all

11. Do the following statement apply to your company? “The number of required IT equipment, functionalities, and quality of service are optimized in order to reduce environmental impact.”

- ○ Extremely
- ○ Moderately
- ○ Not at all

12. Do the following statement apply to your company? “Routing is made energy aware and offers possibilities to choose the most energy efficient route instead of the shortest path.”

- ○ Extremely
- ○ Moderately
- ○ Not at all

V_4:

13. Has your company adopted any documented reference architecture (with guiding principles for designing new services/products) aimed to minimize environmental impact?

- ○ True
- ○ False

14. Does your company have any sustainable development-related training and communication activities for employees?

- ○ True
- ○ False

15. Does your company promote the use of audio and video conferencing facilities reduce travel?

- ○ True
- ○ False

V_5:

16. Does the following statement apply to your company?

"*Ensure a strict implementation of an e-waste policy for the reuse or recycling of ICT equipment to minimize environmental and social hazards after disposal*."

- ○ Extremely
- ○ Moderately
- ○ Not at all

17. Does your company have any collection and recovery (e.g. reuse, repairing, remanufacturing) channels (subcontractors) that can reduce the amount of waste sent to landfill?

- ○ True
- ○ False

The knowledge base in this research is constructed after an in-depth literature review, critical analyses of existing environmental performance assessment models and primarily guided by the EU Draft Background Report for the development of an EMAS Sectoral Reference Document on "Best Environmental Management Practice in the Telecommunications and ICT Services Sector" [31]. Thus, questions numbered from 1 to 3 relate to the V_1 - Equipment procurement compliant with Green ICT guidelines and the optimization of enterprise operations; questions numbered from 4 to 8 are for the V_2 - Energy performance improvements and monitoring towards the use of alternative energy resources; questions numbered from 10 to 12 are for the V_3 - Energy- aware network engineering adherence; and questions numbered from 13 to 15 are for the V_4 - Social commitment; V_5 - Waste management.

As it can be seen, the knowledge base has 5 V_j parent categories and 17 A_j^i antecedent attributes. Each category consists of antecedent attributes that comprise a set of questionnaire items that users will need to answer. In order to provide mathematical handling of various input data types and uncertainties, a set of available referential values is described as {(High, 0.0), (Medium, 0.0), (Low, 0.0)}. It is important to mention that the research has followed several iterations in refining the knowledge categorization in the knowledge base: initially, there are 8 independent parent categories, which would lead to 3^8 = 6561 cases of combinations to consider, adding additional complications and overhead. Subsequently, the total number of categories has been streamlined into 5 categories for simplicity and integrity purposes. The total ER index is calculated (Eq. 14), by aggregating N=5 number of parent categories, which in turn consist of $\sum_{i=1}^{N} A_j^i$ aggregation of corresponding antecedents. A_j^i represents the corresponding questionnaire item for each V_j category.

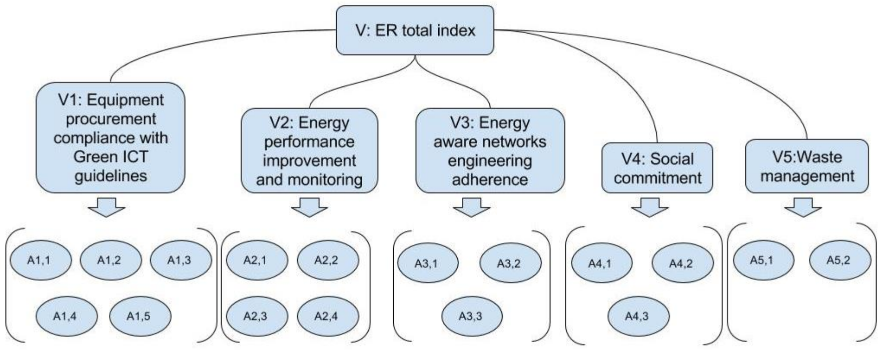

Fig. 2. Knowledge base tree

Having 5 antecedent parent categories with 3 referential values result in 243 total number of rules. A total number of 243 rules is determined based on the number of categories $X = \{x_i; i = 1 \dots T\}, where\ T = 5$ and 3 referential attributed (high, medium, low): $3^5 = 243$. To enumerate all possible combinations, the R language for statistical computing and graphics is used (function - expand.grid(1:3,1:3,1:3,1:3,1:3). Table 2 below is the extract of a matrix with 243 inference rules:

Rule id	Rule weight	IF	THEN
1	1	V_1 is H & V_2 is H & V_3 is H & V_4 is H & V_5 is H	V is {H} or V is {(H, 1.0), (M, 0.0), (L, 0.0)}
2	1	V_1 is M & V_2 is H & V_3 is H & V_4 is H & V_5 is H	V is {H} or V is {(H, 0.9), (M, 0.1), (L, 0.0)}
3	1	V_1 is L & V_2 is H & V_3 is H & V_4 is H & V_5 is H	V is {H} or V is {(H, 0.8), (M, 0.2), (L, 0.0)}

4	1	V_1 is H & V_2 is M & V_3 is H & V_4 is H & V_5 is H	V is {H} or V is {(H, 0.8), (M, 0.2), (L, 0.0)}
...	...	...	...
243	1	V_1 is L & V_2 is L & V_3 is L & V_4 is L & V_5 is L	V is {L} or V is {(H, 0.0), (M, 0.0), (L, 1.0)}

Table 2. Rule base matrix

Here, {H} is a high, {M} is a medium and {L} is a low degree of Environmentally Responsibility index. Table 2 describes two different approaches for producing the total index: ER is {H} with implicit uncertainty handling and ER is {(H, 1.0), (M, 0.0), (L, 0.0)} with explicit uncertainty handling (Eq. 4). It has been decided to keep the weights to be one for all the rules, i.e. assigning the same importance to each rule. Examples of a belief rule taken from Table 2 are:

*R1: IF Energy performance improvement and monitoring is **High** and Energy performance improvement and monitoring is **High** and Energy aware networks engineering adherence is **High** and Social commitment is **High** and Waste management is **High** THEN ER index is High*

*R2: IF Energy performance improvement and monitoring is **Low** and Energy performance improvement and monitoring is **High** and Energy aware networks engineering adherence is **Medium** and Social commitment is **Low** and Waste management is **Medium** THEN ER index is Medium*

*R3: IF Energy performance improvement and monitoring is **Low** and Energy performance improvement and monitoring is **High** and Energy aware networks engineering adherence is **Low** and Social commitment is **Low** and Waste management is **Low** THEN ER index is Low*

Here, belief degrees are attached to three referential values and weighted equal. Upon inference completion, the total ER index ($\sum_{i=1}^{N} V_n$) is generated with the following breakdown: Initial level for 0-20% range, Beginning 20-40%, Improving 40-60%, Succeeding 60-80% and Leading 80-100% accordingly. The total ER index is displayed without uncertainties in a single deterministic value in percentages, i.e. V is {H} or V is {M} or V is {L}, as it shown in Fig. 3. Additionally, output result of the toolkit developed shows the total ER index score and sub-category score breakdown in %.

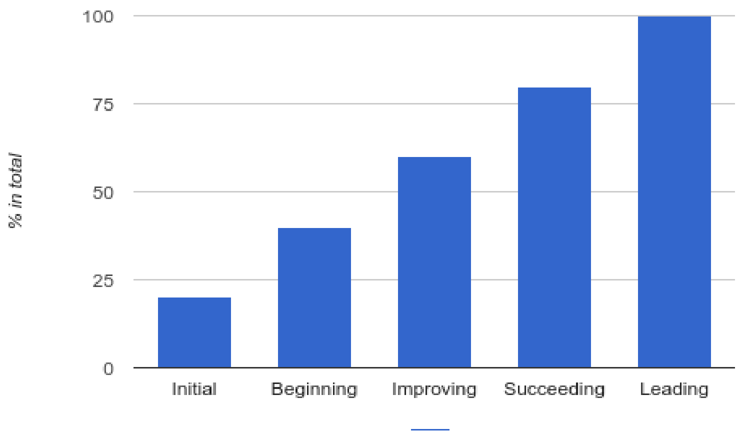

Fig. 3. Maturity levels

An Environmental Responsibility assessment system toolkit is intended to be used by small and medium-sized enterprises' regular employees or ICT department representatives. Therefore, all aggregated consequent numbers are rounded to nearest decimal and end-users are notified of the estimate (not precise) figures, due to nature ER index value.

3.1.2 Environmental Responsibility toolkit

As a proof of concept, a Java web-application "Environmental Responsibility Toolkit for SMEs" has been developed (http://demo1-ersme.rhcloud.com), with a JBoss Drools inference engine to provide the reasoning mechanism. The inference engine has been populated with rules described in Table 2, where an inference starts iteratively searching for the pattern-match of an input and if-then clause. If it is true, the relevant then clause is fired triggering an appropriate action.

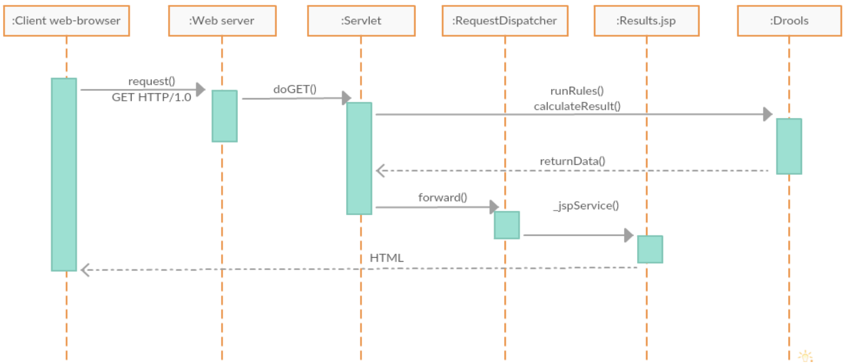

Fig. 4. Web-based ER assessment sequence diagram

The assessment itself encompasses a questionnaire with 17 items to be responded with predefined degrees of uncertainty for each rule, defined in Table 2. Upon completion of the questionnaire, the results are automatically analyzed and the page is displayed with a total ER index score and sub-category score breakdown. Also, based on the results, an individualized set of recommendations to improve the Environmentally Responsibility level are presented (outside the scope of this chapter but details could be found in [36])). Recommendations are based on EU Draft Background Report for the development of an EMAS Sectoral Reference Document "Best Environmental Management Practice in the Telecommunications and ICT Services Sector" [31].

4 BRB and FIS performance comparison

This section presents validation results of BRB system developed with a Fuzzy logic reasoning based approach for the Environmentally Responsibility assessment. The modeling has been performed using Matlab Fuzzy Logic Toolbox. Comparison between BRB and Fuzzy approach results has been performed and proved the validity of a proposed BRB technique.

In the last two decades, fuzzy logic theory application has increased significantly, which was firstly introduced by L.A. Zadeh [32]. Fuzzy logic (FL) comes from theory of fuzzy sets, where classes of input objects have unsharp boundaries with a certain degree of belief, which is in a wider sense can be described as a theory of multivalued logic. FL has been widely deployed in different applications of decision support, industrial process controls and consumer products selection. A crucial significance of that approach is the use of linguistic variables in describing complex systems, e.g. descriptive words in human-readable and comprehensible format [33].

4.1 Fuzzy Logic design

A basic fuzzy logic system consists of three component: fuzzifier, FIS and defuzzifier. A fuzzifier finds a mapping between input variables values into a fuzzy set and defuzzifier does a reverse operation of mapping set of output values into a crisp value. Hence, fuzzy logic is a helpful tool to map an input space to an output space. The primary mechanism for doing this resides in FIS through the list of if-then rules. An architectural view of basic fuzzy system is shown in Fig. 5:

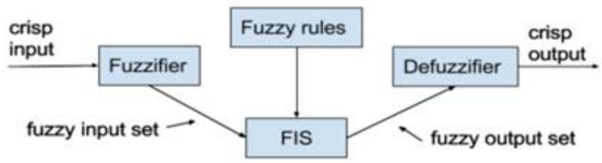

Fig. 5. Fuzzy logic system design

There are three steps in a fuzzy inference process: fuzzification, fuzzy rule inference, and defuzzification. The algorithmic steps of a fuzzy logic system life cycle are as follows:

1. Decide on linguistic variables and notations for input and output variables;
2. Determine pertinent membership functions for each input and output variables;

3. Construct knowledge base in rules format;
4. Fuzzification: convert crisp data into fuzzy data sets using membership functions;
5. Fuzzy rules inference: rules evaluation in the rule base and the results set combination;
6. Defuzzification: convert fuzzy output values into crisp data.

The Mamdani type inference has been deployed for building the model, which expects the output membership functions to be fuzzy sets. The input variables are fuzzified with three linguistic attributes “low”, “medium” and “high”, as previously defined in the BRB system, with the *gaussmf* membership function (MF) in a range [0 100]. The output variable is described with *trimf* MF with “poor”, “average” and “good” attributes. The model consists of 3 rules, defined in accordance with the BRB system. The Surface Viewer of the Matlab Fuzzy Logic Toolbox shows the graphical mapping between any two inputs and an output.

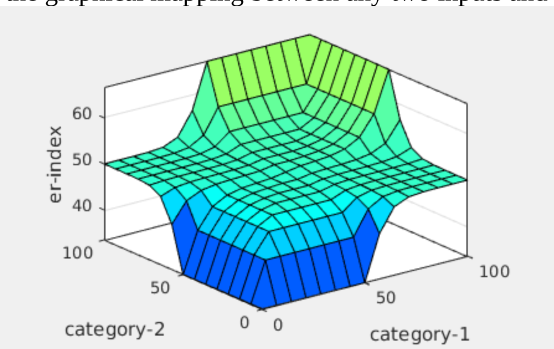

Fig. 6. Surface view of ER SME assessment

4.2 Results and comparison

The Belief Rule-Based approach is compared with FIS in this section. In order to verify the validity of the methodology chosen in ER assessment research, 100 simulations with randomized input variables (answers to questions) were carried out. The chart below presents results of the simulations, an additional mean value is included in comparative analysis as a benchmark.

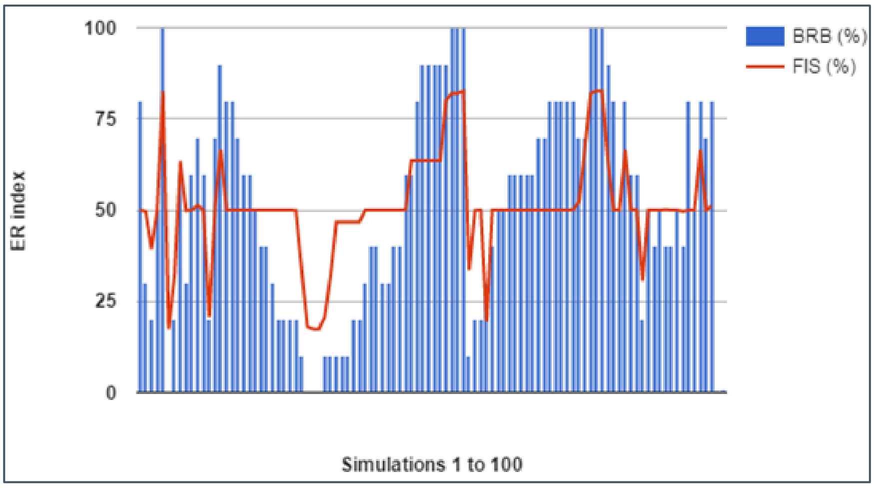

Fig. 7. Methods comparison

It is observed that the results of the fuzzy approach are close to the calculated mean value for almost all the experiments. Results of two methods are within the range of the standard deviation. The standard deviation value could be used to calculate the maximum, minimum and mean values. It is found that FIS performs better for the range of values closer to the mean value (calculated mean value) but not for the maximum nor the minimum values. Per category effect and consequence are not handled in output variables generated based on mean value calculations. For example, when the "Category 1 - Equipment procurement compliant with Green ICT guidelines and the optimization of enterprise operations" accomplishes its maximum value, that implies a positive degree of awareness of an organization on environmental issues, hence result in BRB in simulation-1 is higher compared to FIS and mean calculations. Also, when at least one of the input variables is equal to zero, BRB approach demonstrates a lesser output variable, which is legitimate: failing to address even one aspect of a problem, causes the whole case status unsteady and unreliable.

4.3 Statistical Analysis and Significance Tests

Significance test has been performed to determine if the BRB approach and FIS theory produce significantly different results. As a first step, we need to test the assumption that the samples come from normal distributions. From the plots below it is evident that BRB (blue) approximately follows a straight line, indicating approximate normal distribution. The FIS sample (orange colored) shows an increasing departure from normality in the lower tail.

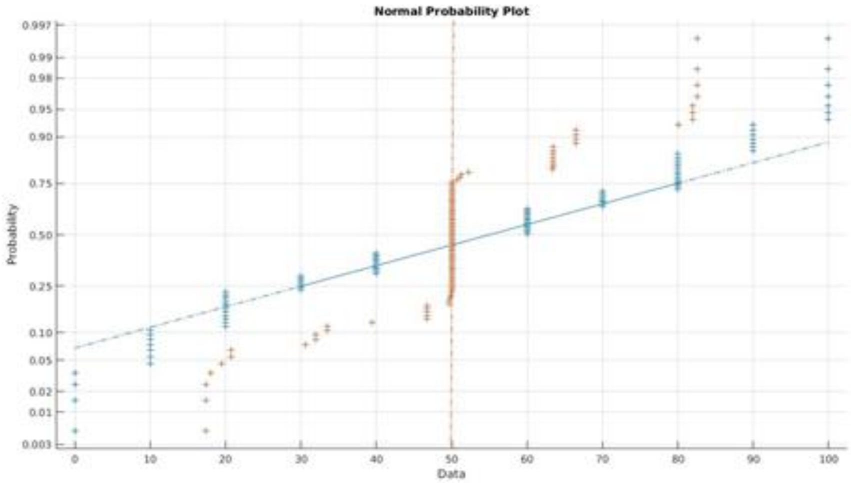

Fig. 8. Normal distribution probability for BRB and FIS

The difference between BRB and FIS is evident. Next, we need to set up hypotheses and evaluate whether the difference between BRB and FIS is significant. In this statistical test, μ_1 is the mean score for BRB while μ_2 is the mean score for FIS. H_0 is the null hypothesis where μ_1 equals to μ_2 while H_1 is the alternative hypothesis where μ_1 is not equal to μ_2. A two-tail z-test is conducted at a level of confidence of 0.05. Difference between BRB and FIS is evident.

$$H_0: \mu_1 = \mu_2 \ ; H_1: \mu_1 \neq \mu_2, \alpha=0.05 \tag{15}$$

The Table 3 below shows a statistical analysis of the two independent data samples. Because both data samples are large (>30), a z-test has been chosen opposed to t-test. The calculated variance values are different for BRB (819.43) and FIS (194.70) and thus we shall conduct a two-tail z-test for two samples with unequal variances at a level of confidence of 0.05.

TABLE 3. z-Test: two Sample for Means

	BRB	*FIS*
Mean, μ	52.32	51.01
Known Variance, *σ*	819.43	194.70
No of observations (n)	99.00	99.00
Hypothesized Mean Difference	0.00	
Z value	0.41	
P(Z<=z) one-tail	0.34	
z Critical one-tail	1.64	
p-value (Z<=z) two-tail	0.68	
z Critical two-tail	1.96	

The p-value is a probability that measures the evidence against the null hypothesis. The p-value in our research is greater than α, so we fail to reject H0. This means that BRB and FIS approaches do not generate significantly different results. However, as we can see from the Table 3, the variances of two populations are unequal (BRB is 4 times higher than FIS). Again, the hypotheses-test indicates that there is not enough evidence to reject the null hypothesis that the two batch z-score is equal at the 0.05 significance level. This failure may reflect normality in the population or it may reflect a lack of strong evidence against the null hypothesis due to the small sample size.

A two-tail z-test for the means of two independent samples with unequal variances investigates whether two independent samples come from normal distributions with unequal variances and the same mean values. For a hypotheses test quality assurance of two data samples have been tested also using the two-sample Kolmogorov-Smirnov test. The function *kstest2(columnBRB, columnFIS)* returned the value equal to 1. The result rejects the hypothesis that the data in BRB and FIS samples are from the same continuous distribution at the 5% significance level. This confirms our assumption in two approaches heterogeneity.

To conclude, the BRB approach deployed in this research dedicated to small and medium-sized enterprises to assess their Environmentally Responsibility level generates correlative, well balanced and sensible results compared to FIS approach. So the observed difference between the sample means (52.32 – 51.01) is not convincing enough to say that BRB and FIS approaches generate notably different consequences. Although, the test only performs comparison between mean values and does not focus on such a substantial difference in variances. The most likely explanation of z-test result is that BRB approach, in contrast to FIS, deploys rule based context-adapted inference procedures for a total consequent variables calculation.

4 Conclusions

This research proposes the use of a Belief Rule-Based approach to assess an enterprise's level commitment to environmental issues. Participating companies have to complete a structured questionnaire of the Environmental Responsibility BRB assessment system developed. An automated analysis of their responses (using the Belief Rule-Based approach) determines their environmental responsibility level. This is followed by a recommendation on how to progress to the next level. The recommended best practices will help promote understanding, increase awareness, and make the organization greener. It is posited that such a system generates well balanced, sensible and context adapted results. The aim of the Environmentally Responsibility Assessment System is to help small and medium-sized enterprises focus on making improvements on more sustainable business operations.

Future work recommendations are drawn from the validation by experts, focus groups, and the target SM, which are: 1) test the usefulness of the assessment in practice and benchmark the results among a pool of similar type of enterprise respondents; 2) include required capital investment amount, payback period and cost saving for each recommended activity; 3) provide specialized assessment and recommendation roadmaps for a participating organization's industrial sector (manufacturing, non-manufacturing); 4) develop a paid version with more questions and recommendations for more accurate ER assessment estimations, where the users would be able to save their scores, export results and track their progress.

The key limitations of this study are: 1) assessment does not take into account regional differences among potential participating organizations; 2) assessment model is not sector-specific. The final limitation extracted from validation sessions is the assessment model applicability to medium-sized enterprises, rather than small and micro organizations. This is due to the type of content and level of questions asked in the assessment process. The assessment model and recommendations would benefit from being evaluated by more Green ICT and Sustainability experts and this could be potentially addressed in the future research. Furthermore, the Forward chaining inference algorithm is considered to be less powerful than alternative methods like evidential reasoning, D-S theory or Bayesian networks etc. The ER assessment model could be improved by integrating and enhancing the current forward chaining logic with uncertainty handling mechanisms.

Acknowledgments This work has been conducted as part of the Erasmus+ Master program PERCCOM (Pervasive Computing and Communications for Sustainable Development). Thus, author would like to thank the Erasmus Mundus program and the European Union for the opportunity to participate in this program and complete this study. The authors are grateful to referees for their feedback comments that have helped to improve the quality of the system.

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