International Standard ISO 9001 an Artificial Intelligence View

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Keywords: International Standard ISO 9001, Knowledge Representation and Reasoning, Logic Programming, Artificial Neural Networks.

Abstract: ISO 9001 is recognized as a Quality Management Systems standard, i.e., it is the primary phase of a process of constant enhancement that will provide an organisation with the necessary management tools to improve working practices. Indeed, it provides a framework and a set of principles aimed at ensuring a common sense approach to the management of an organization in order to consistently satisfy customers and other stakeholders. Therefore, and in order to add value to ISO 9001, this work focuses on the development of a decision support system, which will allow companies to be able to meet the needs of customers by fulfilling requirements that reflect either the effectiveness or the non-effectiveness of an organization. The procedures for knowledge representation and reasoning used are based on an extension to the Logic Programming language, allowing the handling of incomplete, contradictory and even forbidden data, information and/or knowledge. The computational framework is centred on Artificial Neural Networks to evaluate customer's satisfaction and the degree of confidence that one has on such a happening.

1 INTRODUCTION

Organizations, either in the business sphere or in the scope of the public sector, owe their existence to their customer´s prospects in terms of commodities and services and, the last but not the least, are also indebted to reward their stakeholders. Quality Management (QM) is one of the practices that can bring competitive advantages to businesses, i.e., the implementation of QM effectively influences enterprises performance (Kaynak, 2003; Parast et al., 2011; Shahin and Dabestani, 2011). Indeed, corporations that implement QM aim to add value to their customers, i.e., improvement of processes and products quality leads to reduce their costs and increase their profits (Kaynak, 2003; Pignanelli and Csillag, 2008).

The ISO 9001 standard do not refers to the compliance with a given goal or result. This standard does not aim to measure the quality of the enterprises' products or services but rather point out the need to systematize a set of procedures and document such implementation (Braun, 2005). The implementation of ISO 9001 standard is voluntary, although in some sectors it has become quasi-obligatory (Braun, 2005).

The International Standard ISO 9001 is applicable to all sectors and organizations, regardless of their type, size, product, or service. The standard is interpretative, not prescriptive, offering an independent system of managing and evaluation of companies' performance, allowing improving either their management practices or their global recognition. ISO 9001 is based on 8 (eight) Quality Management Principles, which are incorporated within the requirements of the standard, and can be applied to develop organizational performance (IPQ, 2008), in terms of:

- Customer focus;
- Leadership;
- Involvement of people;
- Process approach;
- System approach to management;
- Continual improvement;
- Factual approach to decision making; and
- Mutually beneficial supplier relationships.

Neves J., Fernandes A., Gomes G., Neves M., Abelha A. and Vicente H..
International Standard ISO 9001 an Artificial Intelligence View.
DOI: 10.5220/0005328904210428
In *Proceedings of the 17th International Conference on Enterprise Information Systems* (ICEIS-2015), pages 421-428
ISBN: 978-989-758-096-3

The derivative benefits are no less important, and include:

- Enhanced reputation;
- Repeat business;
- Ability to compete more effectively globally, both on quality and price;
- Access to new markets;
- Improved customer and supplier relationships;
- Improved employee morale; and
- Improved management control.

According to Tarí (Tarí, 2012) these benefits may be catalogued into internal and external. The former ones include improvements in corporate processes, having positive effects on operational and work forces issues (e.g. increase in productivity, improvement in efficiency, reduction in costs, training). The external benefits, in turn, relate to effects on customers and society in general (e.g. customer satisfaction, better relationships with stakeholders, improved image).

This work reports the founding of a computational framework that uses knowledge representation and reasoning techniques to set the structure of the information and the associate inference mechanisms. We will centre on a Logic Programming (LP) based approach to knowledge representation and reasoning (Neves, 1984; Neves et al., 2007), complemented with a computational framework based on Artificial Neural Networks (Cortez et al., 2004, Caldeira et al., 2011, Vicente et al., 2013). The requirements of ISO 9001 that can better predict the efficacy (or lack of efficacy) of an organization were selected (IPQ, 2012). We take as example a company in the area of training where two management indicators, namely complaints and customer satisfaction were used and attained by questionnaires. Both indicators consider several items, namely Trainee´s General Information; Trainee´s Complaints; Trainee´s Satisfaction; Quality of Support Materials; and Inquiries of Trainee´s Satisfaction, that will be described later.

2 KNOWLEDGE REPRESENTATION AND REASONING

Many approaches for knowledge representation and reasoning have been proposed using the Logic Programming (LP) paradigm, namely in the area of Model Theory (Kakas et al., 1998; Gelfond and Lifschitz, 1988; Pereira and Anh, 2009), and Proof Theory (Neves, 1984; Neves et al., 2007). We follow the proof theoretical approach and an extension to the LP language, to knowledge representations and reasoning. An Extended Logic Program (ELP) is a finite set of clauses in the form:

$$p \leftarrow p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m \qquad (1)$$

$$?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m)\ \ (n, m \geq 0) \qquad (2)$$

where "*?*" is a domain atom denoting falsity, the p_i, q_j, and p are classical ground literals, i.e., either positive atoms or atoms preceded by the classical negation sign $\neg$ (Neves, 1984). Under this emblematic formalism, every program is associated with a set of abducibles (Kakas et al., 1998; Pereira and Anh, 2009) given here in the form of exceptions to the extensions of the predicates that make the program. Once again, LP emerged as an attractive formalism for knowledge representation and reasoning tasks, introducing an efficient search mechanism for problem solving.

Due to the growing need to offer user support in decision-making processes some studies have been presented related to the qualitative models and qualitative reasoning in Database Theory and in Artificial Intelligence research (Halpern, 2005; Kovalerchuck and Resconi, 2010). With respect to the problem of knowledge representation and reasoning in LP, a measure of the *Quality-of-Information* (*QoI*) of such programs has been object of some work with promising results (Lucas, 2003; Machado et al., 2010). The *QoI* with respect to the extension of a predicate *i* will be given by a truth--value in the interval [0,1], i.e., if the information is *known* (*positive*) or *false* (*negative*) the *QoI* for the extension of $predicate_i$ is 1. For situations where the information is unknown, the *QoI* is given by:

$$QoI_i = \lim_{N \to \infty} \frac{1}{N} = 0 \qquad (N \gg 0) \qquad (3)$$

where N denotes the cardinality of the set of terms or clauses of the extension of $predicate_i$ that stand for the incompleteness under consideration. For situations where the extension of $predicate_i$ is unknown but can be taken from a set of values, the *QoI* is given by:

$$QoI_i = {}^{1}/_{Card} \qquad (4)$$

where *Card* denotes the cardinality of the *abducibles* set for *i*, if the *abducibles* set is disjoint. If the *abducibles* set is not disjoint, the *QoI* is given by:

$$QoI_i = \frac{1}{C_1^{Card} + \cdots + C_{Card}^{Card}} \qquad (5)$$

where C_{Card}^{Card} is a card-combination subset, with *Card* elements. The next element of the model to be considered is the relative importance that a predicate assigns to each of its attributes under observation, i.e., w_i^k, which stands for the relevance of attribute *k* in the extension of $predicate_i$. It is also assumed that the weights of all the attribute predicates are normalized, i.e.:

$$\sum_{1\le k\le n} w_i^k = 1, \forall_i \qquad (6)$$

where $\forall$ denotes the universal quantifier. It is now possible to define a predicate's scoring function $V_i(x)$ so that, for a value $x = (x_1, \cdots, x_n)$, defined in terms of the attributes of $predicate_i$, one may have:

$$V_i(x) = \sum_{1\le k\le n} w_i^k \times QoI_i(x)/n \qquad (7)$$

allowing one to set:

$$predicate_i(x_1, \cdots, x_n) :: V_i(x) \qquad (8)$$

It is now possible to engender the universe of discourse, according to the information given in the logic programs that endorse the information about the problem under consideration, according to productions of the type:

$$predicate_i - \bigcup_{1\le j\le m} clause_j(x_1, \cdots, x_n) :: QoI_i :: DoC_i \qquad (9)$$

where U and m stand, respectively, for "set union" and the cardinality of the extension of $predicate_i$. On the other hand, DoC_i denotes one's confidence on the attribute`s values of a particular term of the extension of $predicate_i$, whose evaluation will be illustrated below. In order to advance with a broad-spectrum, let us suppose that the Universe of Discourse is described by the extension of the predicates:

$$f_1(\cdots), f_2(\cdots), \cdots, f_n(\cdots) \ \ where \ \ (n \ge 0) \qquad (10)$$

Assuming we have a clause that is mapped into a case, that clause has as argument all the attributes that make the case. The argument values may be of the type unknown or members of a set, may be in the scope of a given interval or may qualify a particular observation. Let us consider the following clause where the second argument value may fit into the interval [3,5] with a domain of [0,8], the value of the third argument is unknown, which is represented by the symbol $\perp$, with a domain that ranges in the interval [5,15], and the first argument stands for itself, with a domain that ranges in the interval [0,3]. Let us consider that the case data is given by the extension of predicate f_1, given in the form:

$$f_1: x_1, x_2, x_3 \rightarrow \{True, False\} \qquad (11)$$

where "*{*" and "*}*" is one´s notation for sets, where "*0*" and "*1*" denote, respectively, the truth values "*false*" and "*true*". One may have:

{

$$\neg f_1(x_1, x_2, x_3) \leftarrow not\ f_1(x_1, x_2, x_3)$$
$$f_1(\underbrace{2,\ \ [3,5],\ \ \perp}_{attribute`s\ values}) :: 1 :: DoC$$
$$\underbrace{[0,3]\ [0,8]\ [5,15]}_{attribute`s\ domains}$$

…

}

Once the clauses or terms of the extension of the predicate are established, the next step is to transform all the arguments, of each clause, into continuous intervals. In this phase, it is essential to consider the domain of the arguments. As the third argument is unknown, its interval will cover all the possibilities of the domain. The first argument speaks for itself. Therefore, one may have:

{

$$\neg f_1(x_1, x_2, x_3) \leftarrow not\ f_1(x_1, x_2, x_3)$$
$$f_1(\underbrace{[2,2],\ \ [3,5],\ \ [5,15]}_{attribute`s\ values\ ranges}) :: 1 :: DoC$$
$$\underbrace{[0,3]\ \ \ [0,8]\ \ \ [5,15]}_{attribute`s\ domains}$$

…

}

Now, one is in position to calculate the *Degree of Confidence* for each attribute that makes the term´s arguments (e.g. for attribute two it denotes one's confidence that the attribute under consideration fits into the interval [3,5]). Next, we set the boundaries of the arguments intervals to be fitted in the interval [0,1] according to the normalization procedure given in the procedural form by $(Y - Y_{min})/(Y_{max} - Y_{min})$, where the Y_s stand for themselves.

{

$$\neg f_1(x_1, x_2, x_3) \leftarrow not\ f_1(x_1, x_2, x_3)$$
$$x_1 = \left[\frac{2-0}{3-0}, \frac{2-0}{3-0}\right], x_2 = \left[\frac{3-0}{8-0}, \frac{5-0}{8-0}\right],$$
$$x_3 = \left[\frac{5-5}{15-5}, \frac{15-5}{15-5}\right]$$
$$f_1\left(\underbrace{[0.67, 0.67], [0.38, 0.62], [0,1]}_{\substack{attribute`s\ values\ ranges\\ once\ normalized}}\right) :: 1 :: DoC$$
$$\underbrace{[0,1]\ \ \ \ \ \ \ \ [0,1]\ \ \ \ [0,1]}_{\substack{attribute`s\ domains\\ once\ normalized}}$$

…

}

The *Degree of Confidence* (*DoC*) is evaluated using the equation $DoC = \sqrt{1 - \Delta l^2}$, as it is illustrated in Figure 1, where Δl stands for the length of the argument´s intervals, once normalized.

{

$$\neg f_1(x_1, x_2, x_3) \leftarrow not\ f_1(x_1, x_2, x_3)$$
$$f_1\left(\underbrace{1,\ \ \ \ \ \ \ \ 0.968,\ \ \ \ \ 0}_{attribute`s\ confidence\ values}\right) :: 1 :: 0.656$$
$$\underbrace{[0.67, 0.67][0.38, 0.62]\ [0,1]}_{\substack{attribute`s\ values\ ranges\\ once\ normalized}}$$

$$\underbrace{[0,1] \quad [0,1] \quad [0,1]}_{attribute`s\ domains\ once\ normalized}$$

…
}

where the *DoC's* for $f_1(1,\ 0.968,\ 0)$ is evaluated as $(1+0.968+0)/3 = 0.656$, assuming that all the argument's attributes have the same weight.

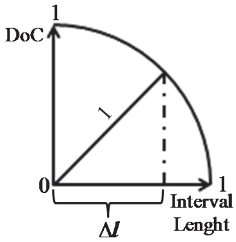

Figure 1: Computing the Degree of Confidence values.

3 A CASE STUDY

In order to exemplify the applicability of our ideal, we will look at the relational database model, since it provides a basic framework that fits into our expectations (Liu and Sun, 2007), and is understood as the genesis of the *LP* approach to Knowledge Representation and Reasoning (Neves, 1984).

As a case study, consider the scenario where a relational database is given in terms of the extensions of the relations depicted in Figure 2, which stands for a situation where one has to manage information about trainees' satisfaction evaluation. Under this scenario some incomplete and/or default data is also available. For instance, in the *Trainees' Satisfaction* database, the opinion of trainee 1 about *Support Materials* is unknown, while the *Inquiries of Trainees' Satisfaction* ranges in the interval [16, 21]. In *Trainees' Complaints* database, 0 (zero) denotes absence and 1 (one) denotes existence of complaints. The issues of *Quality of Support Materials* and *Inquiries of Trainees' Satisfaction* databases range in the interval [0, 5], i.e., range between Inadequate (0) and Excellent (1). In *Trainee Situation* Column of the *Trainees' Satisfaction* database 0, 1 and 2 stands respectively for *dropped out*, *ongoing* and *course finished*. The values presented in *General Opinion about the Course* and *Willingness to Recommend the Company* columns ranges in the interval [0, 10]. In the former case 0 (zero) stands for *Strongly Negative Opinion* and 10 (ten) denotes a *Strongly Positive Opinion*. In the last case 0 (zero) stands for *None* and 10 (ten) denotes *Absolutely Sure*. The values presented in the remaining columns are the sum of the respective databases, ranging between [0, 6], [0, 10] and [0, 25] respectively for *Complaints*, *Support Materials* and *Inquiries of Trainees' Satisfaction* columns.

Now, we may consider the relations given in Figure 2, in terms of the *satisfaction* predicate, given in the form:

Trainees' General Information

#	Age	Gender	Trainee Situation
1	27	Female	finished
2	32	Male	dropped out
…	…	…	…
n	21	Female	ongoing

Trainees' Complaints

#	Billing	Trainer	Infrastructures	Customer Service	Sale Arguments	Support Materials
1	0	0	0	0	0	0
2	1	1	1	0	1	1
…	…	…	…	…	…	…
n	1	0	1	0	0	0

Trainees' Satisfaction

#	Trainee Situation	General Opinion about the Course	Willingness to Recommend the Company	Complaints	Support Materials	Inquiries of Trainees' Satisfaction
1	2	9	8	0	⊥	[16,21]
2	0	3	2	5	4	12
…	…	…	…	…	…	…
n	1	[8,9]	⊥	2	8	22

Quality of Support Materials

#	Syllabus	Materials
1	⊥	⊥
2	2	2
…	…	…
n	4	4

Inquiries of Trainees' Satisfaction

#	Guidance	Trainer	Image of the Training Course	Customer Service	Methodologies
1	4	4	⊥	4	4
2	2	2	3	3	2
…	…	…	…	…	…
n	5	5	3	4	5

Figure 2: Extension of the Relational Database model.

$$satisfaction: T_{trainee}S_{ituation}, G_{eneral}O_{pinion\ about\ the\ course}, W_{illingness\ to}R_{ecommend\ the}C_{ompany}, Compl_{aints}, S_{upport}M_{aterials}, I_{nquiries\ of}T_{rainees}, S_{atisfaction} \rightarrow \{0,1\}$$

where 0 (zero) and 1 (one) denote, respectively, the truth values *false* and *true*. It is now possible to give the extension of the predicate *satisfaction*, in the form:

$$
\begin{array}{l}
\{ \\
\quad \neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS) \\
\quad satisfaction\left(\underbrace{2,\ 9,\ 8,\ 0,\ \perp,\ [16,21]}_{attribute`s\ values}\right) :: 1 :: DoC \\
\qquad\qquad\quad \underbrace{[0,2][0,10][0,10][0,6]\ [0,10]\ [0,25]}_{attribute`s\ domains} \\
\quad \ldots \\
\}
\end{array}
$$

In this program, the first clause denotes the closure of predicate *satisfaction*. The next clause corresponds to the trainee 1, taken from the extension of the satisfaction relation presents in Figure 2. Moving on, the next step is to transform all the argument values into continuous intervals and then normalize the predicate´s arguments in order to obtain the Degree of Confidence of the satisfaction predicate. One may have:

$$
\begin{array}{l}
\{ \\
\quad \neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS) \\
\quad satisfaction\left(\underbrace{[2,2], [9,9], [8,8], [0,0], [0,10], [16,21]}_{attribute`s\ values\ ranges}\right) :: 1 :: DoC \\
\qquad\qquad\quad \underbrace{[0,2][0,10][0,10][0,6]\ [0,10]\ \ [0,25]}_{attribute`s\ domains} \\
\quad \ldots \\
\}
\end{array}
$$

The logic program referred to above, is now presented in the form:

$$
\begin{array}{l}
\{ \\
\quad \neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS) \\
\quad satisfaction\left(\underbrace{1,\ 1,\ 1,\ 1,\ 0,\ 0.98}_{attribute`s\ confidence\ values}\right) :: 1 :: 0.83 \\
\qquad\qquad\quad \underbrace{[1,1][0.9,0.9][0.8,0.8][0,0][0,1][0.64,0.84]}_{attribute`s\ values\ ranges\ once\ normalized} \\
\qquad\qquad\quad \underbrace{[0,1]\ \ [0,1]\ \ \ [0,1]\ \ [0,1][0,1]\ \ [0,1]}_{attribute`s\ domains\ once\ normalized} \\
\quad \ldots \\
\}
\end{array}
$$

where its terms make the training and test sets of the Artificial Neural Network given in Figure 3.

4 ARTIFICIAL NEURAL NETWORKS

Several studies have shown how Artificial Neural Networks (ANNs) could be successfully used to model data and capture complex relationships between inputs and outputs (Caldeira et al., 2011, Vicente et al., 2013, Salvador et al., 2013). ANNs simulate the structure of the human brain being populated by multiple layers of neurons. As an example, let us consider the last case presented in Figure 2, where one may have a situation in which information about trainees' satisfaction is needed, given in the form:

$$
\begin{array}{l}
\{ \\
\quad \neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS) \\
\quad satisfaction\left(\underbrace{1,\ [8,9],\ \perp,\ 2,\ 8,\ 22}_{attribute`s\ values}\right) :: 1 :: DoC
\end{array}
$$

$$\underbrace{[0,2][0,10][0,10][0,6][0,10][0,25]}_{attribute`s\ domains}$$

$\Downarrow$ *1st interaction: transition to continuous intervals*

$$\neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS)$$

$$satisfaction\left(\underbrace{[1,1], [8,9], [0,10], [2,2], [8,8], [22,22]}_{attribute`s\ values\ ranges}\right) :: 1 :: DoC$$

$$\underbrace{[0,2][0,10]\ [0,10]\ [0,6]\ [0,10]\ \ [0,25]}_{attribute`s\ domains}$$

$\Downarrow$ *2nd interaction: normalization* $\dfrac{Y - Y_{min}}{Y_{max} - Y_{min}}$

$$\neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS)$$

$$satisfaction\left(\underbrace{[0.5,0.5], [0.8,0.9], [0,1], [0.33,0.33], [0.8,0.8], [0.88,0.88]}_{attribute`s\ values\ ranges\ once\ normalized}\right) :: 1 :: DoC$$

$$\underbrace{[0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]}_{attribute`s\ domains\ once\ normalized}$$

$\Downarrow$ *DoC calculation:* $DoC = \sqrt{1 - \Delta l^2}$

$$\neg\, satisfaction(TS, GO, WR, Compl, SM, ITS) \leftarrow not\ satisfaction(TS, GO, WR, Compl, SM, ITS)$$

$$satisfaction\left(\underbrace{1,\quad 0.995,\quad 0,\quad 1,\quad 1,\quad 1}_{attribute`s\ confidence\ values}\right) :: 1 :: 0.833$$

$$\underbrace{[0.5,0.5][0.8,0.9][0,1][0.33,0.33][0.8,0.8][0.88,0.88]}_{attribute`s\ values\ ranges\ once\ normalized}$$

$$\underbrace{[0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]}_{attribute`s\ domains\ once\ normalized}$$

}

In Figure 3 it is shown how the normalized values of the interval boundaries and their *DoC* and *QoI* values work as inputs to the ANN. The output translates the trainees' satisfaction and the confidence that one has on such a happening. In addition, it also contributes to build a database of study cases that may be used to train and test the ANNs.

In this study 200 samples (i.e. two hundred terms or clauses of the extension of predicate) were considered, coming from a vocational training company of the Lisbon region. The trainees' age average was 25.4 years, ranging from 17 to 32 years old. The gender distribution was 48.3% and 51.7% for male and female, respectively. Regarding trainees' situation, 28.4% completed their training, 12.3% dropped out and 59.3% are attending training.

The dataset used in the training phase it was divided in exclusive subsets through the 10-folds cross validation. In the implementation of the respective dividing procedures, ten executions were performed for each one of them. To ensure statistical significance of the attained results, 30 (thirty) experiments were applied in all tests. The back propagation algorithm was used in the learning process of the ANN. As the output function in the pre-processing layer it was used the identity one. In the other layers we used the sigmoid function.

A common tool to evaluate the results presented by the classification models is the coincidence matrix, a matrix of size $L \times L$, where L denotes the number of possible classes (2 (two) in the present case). Table 1 present the coincidence matrix (the values denote the average of the 30 experiments). A perusal of Table 1 shows that the model accuracy was 95.5% (191 instances correctly classified in 200).

Table 1: The coincidence matrix for the ANN model.

Target	Predict	
	False (0)	True (1)
False (0)	48	4
True (1)	5	143

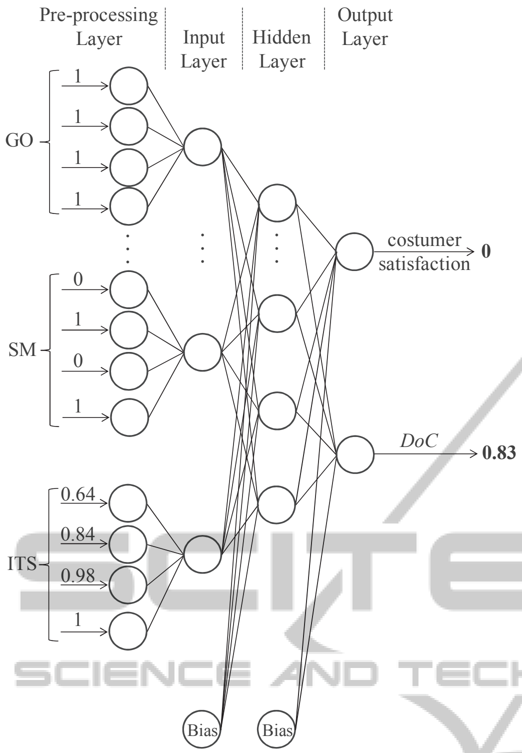

Figure 3: The Artificial Neural Network topology.

5 CONCLUSIONS AND FUTURE WORK

This customer satisfaction assessment system is able to give an adequate response to the need for a good method of customer satisfaction prediction. To go around the problem, more effectively, much more variables must be studied and considered, thus fulfilling important gaps in the existent satisfaction assessment methods.

Being an area filled with incomplete and unknown data it may be tackled by Artificial Intelligence based methodologies and techniques to problem solving. This work presents the founding of a computational framework that uses powerful knowledge representation and reasoning techniques to set the structure of the information and the associate inference mechanisms. Indeed, this method brings a new approach that can revolutionize prediction tools in all its variants, making it more complete than the existing methodologies and tools available.

The knowledge representation and reasoning techniques presented above are very versatile and capable of covering every possible instance by considering incomplete, contradictory, and even unknown data. Indeed, the new paradigm of knowledge representation and reasoning enables the use of the normalized values of the interval boundaries and their *DoC* values, as inputs to the ANN. The output translates the customer satisfaction prediction and the confidence that one has on such a happening.

Future work may recommend that the same problem must be approached using others computational frameworks like Case Based Reasoning (Carneiro et al., 2013), Genetic Programming (Neves et al., 2007), or Particle Swarm (Mendes et al., 2004), just to name a few.

ACKNOWLEDGEMENTS

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the Project Scope UID/CEC/00319/2013.

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