A Fuzzy Logic-based Approach for Assessing the Quality of Business Process Models

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Abstract: Similar to software products, the quality of a Business Process model is vital to the success of all the phases of its lifecycle. Indeed, a high quality BP model paves the way to the successful implementation, execution and performance of the business process. In the literature, the quality of a BP model has been assessed through either the application of formal verification, or most often the evaluation of quality metrics calculated in the static and/or simulated model. Each of these assessment means addresses different quality characteristics and meets particular analysis needs. In this paper, we adopt metrics-based assessment to evaluate the quality of business process models, modeled with Business Process Modeling and Notation (BPMN), in terms of their comprehensibility and modifiability. We propose a fuzzy logic-based approach that uses existing quality metrics for assessing the attainment level of these two quality characteristics. By analyzing the static model, the proposed approach is easy and fast to apply. In addition, it overcomes the threshold determination problem by mining a repository of BPMN models. Furthermore, by relying on fuzzy logic, it resembles human reasoning during the evaluation of the quality of business process models. We illustrate the approach through a case study and its tool support system developed under the eclipse framework. The preliminary experimental evaluation of the proposed system shows encouraging results.

1 INTRODUCTION

A Business Process (BP) model covers different dimensions of an enterprise, mainly functional, organizational, behavioral, and informational (Curtis et al., 1992). Integrating all these dimensions into one *high-quality* model is vital to the persistence of the enterprise (Sánchez-González et al., 2010) and (de Oca et al., 2015). Indeed, such a model will surely facilitate various tasks related to its implementation, deployment, execution, and continuous improvement in short, the BP lifecycle (Weske, 2010). A high-quality BP model will also guarantee its acceptance by end users and thus prevent common BP problems like model reality divide where the modeled and executed processes are not aligned (Schmidt and Nurcan, 2009).

In the literature, BP model quality assessment has been dealt with two main approaches: the application of formal verification methods (Watahiki et al., 2011) and (Morimoto, 2008), or the evaluation of a set of quality metrics calculated on the BP model (Sánchez-González et al., 2010), (Mendling et al., 2012), and (de Oca et al., 2015). Formal methods (e.g., model checking and theorem proving) provide for the verification of behavioral quality properties like progress and deadlock freedom. While they offer objective analysis results that inspire high confidence, their application remains hindered by their complexity. In addition, they do not provide for a qualitative analysis of the model like its complexity, comprehensibility and modifiability; these quality characteristics impact both various tasks of the BP lifecycle and the performance of the enacted BP.

Adopting a qualitative assessment of BP models, researchers proposed to calculate a set of metrics either on the static BP model (e.g. (Sánchez-González et al., 2010), (Mendling et al., 2012), and (de Oca et al., 2015)), or the simulated BP model (e.g. (Heinrich, 2013)). In these works, several quality metrics were used either to assess certain quality characteristics of the BP model itself (case of static model assessment of, for instance, the model complexity, maintainability, Integrity, etc. (Mendling et al., 2012),

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(Makni et al., 2010), and (Sadowska, 2015)) or to predict the BP performance (case of simulated model assessment of, for instance, the mutual impact between the BP and its underlying information system (Heinrich, 2013)). The main challenges in metric-based assessment are: what are the quality characteristics of a BP model, how to relate the metrics to quality characteristics, and how to interpret the values of the metrics.

There is no consensus on the quality characteristics of BP models. Several researchers explored the similarities between processes and software products to adopt the quality characteristics of the latter for business processes. In particular, they adopted the eight model quality characteristics defined in the ISO/IEC 25010 (ISO, 2011) standard quality model, e.g. (Sánchez-GonzáLez et al., 2013) and (Sadowska, 2015). Because the ISO/IEC 25010 quality model does not define any technique for the evaluation of the characteristics, different studies recommended various metrics for assessing the quality of BP models in terms of the proposed characteristics, e.g. (Vanderfeesten et al., 2007a), (Vanderfeesten et al., 2008), (Cardoso et al., 2010), (Sánchez-GonzáLez et al., 2013), and (Sadowska, 2015). In addition, based on the recommended metrics, some researchers proposed the development of an automated framework to evaluate BP model quality, e.g. (Sánchez-González et al., 2010), (Sánchez-González et al., 2011) and (Mendling et al., 2012). The common barrier hindering the development of such a framework is the lack of a consensus about threshold values of the quality metrics, which are required to interpret/evaluate a BP model's quality (Sánchez-González et al., 2010) and (de Oca et al., 2015). This paper addresses this problem through a fuzzy logic-based approach for evaluating the quality of BP models with an emphasis on the comprehensibility and modifiability characteristics. The choice of these two quality characteristics is justified by their importance to guarantee that a BP model can be easily implemented, deployed, and executed. These characteristics are also important when dealing with the continuous improvement of a BP.

The herein proposed approach consists of two essential phases: threshold determination and fuzzy logic application. The first phase applies data mining, specifically decision trees, to determine approximate thresholds for each quality metric. These thresholds will be used for interpreting the comprehensibility or modifiability levels of BP models, modeled in BPMN (ISO, 2013). To this end, we used a BP repository, called "SOA-based Business Process Database"[1], built within our laboratory. This repository contains 1000 business processes of organizations operating in different sectors. The second phase uses the approximate thresholds identified in the first phase along with fuzzy logic (Zadeh, 1965) to assess the quality of a BPMN model. The use of fuzzy logic aims at dealing with the approximate and imprecise nature of the obtained thresholds. Indeed, according to Zadeh, fuzzy logic operates perfectly in an environment of "imperfect information" (Zadeh, 2008).

The proposed approach is implemented in a system that allows the qualitative assessment of BPMN models in terms of comprehensibility and modifiability. To prove the performance of the proposed system, we conducted two types of experiments. The former is done through the proposed system while the second is accomplished in conjunction with students from our college. These preliminary experimental evaluations of the proposed system show encouraging results.

To recapitulate, this paper has a three-fold contributions: (i) identification of approximate thresholds for the different quality metrics to be used for assessing the quality of BP models in terms of comprehensibility and modifiability; (ii) management of the approximate and imprecise nature of the identified thresholds using fuzzy logic; and (iii) proposition of a system that supports the proposed approach.

The remainder of this paper is organized as follows: Section 2 summarizes existing works on the adoption of quality metrics and the definition of their thresholds for the assessment of the comprehensibility and modifiability of BP models. Section 3 presents the proposed approach mining metrics' thresholds. Section 4 shows how we use fuzzy logic to support the approximate and imprecise nature of the defined thresholds. Section 5 illustrates the developed system of BP model quality assessment. Section 6 evaluates the proposed system through two types of experiments. Finally, section 7 summarizes the paper and gives some directions for future work.

2 RELATED WORKS

We first overview the quality metrics used in the literature to assess the comprehensibility and modifiability of BP models. Second, we discuss works on BP model quality assessment.

2.1 Quality Metrics

Different research initiatives adopt quality metrics from the software engineering to assess the quality of BP models. They consider that business processes

[1] https://sites.google.com/site/bposcteam2015/ressources

are a kind of software systems (Reijers and Vanderfeesten, 2004), (Guceglioglu and Demirors, 2005), (Cardoso et al., 2006), and (Sánchez-GonzáLez et al., 2013). The adopted quality metrics are used to assess BP models quality in terms of different characteristics among those defined in the ISO/IEC 25010 quality model (ISO, 2011). In this paper, we use existing metrics to put in place an approach as well as a support system for BP models quality assessment.

To this end, we have conducted a literature review on existing quality metrics for assessing the comprehensibility and modifiability levels of BP models. To shortlist the relevant metrics, we raised the following questions:

1. Is the metric validated either theoretically or empirically?
2. Is there a method for calculating the metric?
3. Is it possible to calculate the metric for BP modeled in BPMN?
4. Is the metric used to evaluate the comprehensibility and/or the modifiability of BP models?

At the end of this study, only a few number metrics were retained. The metrics were eliminated essentially by the first question; indeed, several metrics are adopted from the software engineering domain but they are not validated in the BP domain neither theoretically nor empirically (Muketha et al., 2010). In addition, some metrics were excluded through the third criteria, i.e., they are not adopted for BPMN (Sadowska, 2015). The retained metrics are listed below:

- Control Flow Complexity (CFC) was defined by Cardoso et al. (Cardoso et al., 2006) to measure the complexity introduced by XOR, OR, and AND split constructs.

$$CFC(p) = \sum_{a\in P\wedge a\in XOR-Split} CFC_{XOR}(a) + \sum_{a\in P\wedge a\in OR-Split} CFC_{OR}(a) + \sum_{a\in P\wedge a\in AND-Split} CFC_{AND}(a) \quad (1)$$

  where: $CFC_{XOR}(a) = n$; $CFC_{OR}(a) = 2^n - 1$; $CFC_{AND}(a) = 1$; n=number of outgoing arcs.

- Halstead-based Process Complexity (HPC) was adapted by Cardoso et al. (Cardoso et al., 2006) to estimate the length N, the volume V, and the difficulty D of a process as follows:

$$N = n_1 * \log_2(n_1) + n_2 * \log_2(n_2) \quad (2)$$

$$V = (N_1 + N_2) * \log_2(n_1 + n_2) \quad (3)$$

$$D = (\frac{n_1}{2}) * (\frac{N_2}{n_2}) \quad (4)$$

  where: n_1 is the number of activities, splits and joins, and control-flow elements of a BP. n_2 is the number of data variables manipulated by the BP and its activities. N_1 and N_2 are respectively the total number of elements and data occurrences.

- Interface Complexity (IC) was adapted from information flow metric (Henry and Kafura, 1981) by Cardoso et al. (Cardoso et al., 2006). IC measures the complexity of a process as follows:

$$IC = length * (NbOfInputs * NbOfOutputs)^2 \quad (5)$$

- Number of Activities (NOA) was defined by Cardoso et al. (Cardoso et al., 2006) to measure the number of activities (task and sub-process) of a business process.
- Number of Activities, Joins and Splits (NOAJS) was defined by Cardoso et al. (Cardoso et al., 2006) to measure number of activities, joins and splits of a business process.
- Coefficient of Network Complexity (CNC) was defined by Cardoso et al. (Cardoso et al., 2006). The CNC metric is the ratio of the total number of arcs in a process model to its total number of nodes.
- Cross Connectivity (CC) was defined by Vanderfeesten et al. (Vanderfeesten et al., 2008) to measure the strength of the arcs between process model nodes. The cross connectivity metric expresses the sum of the connectivity between all pairs of nodes in a process model, relative to the theoretical maximum number of paths between all nodes.
- Coupling metric (CP) was defined by Vanderfeesten et al. (Vanderfeesten et al., 2007b) to calculate the coupling degree of a process. This coupling degree depends on the complexity of connections between the tasks and the type of these connections (i.e., AND, OR, XOR).
- Density (D) was defined by Mendling (Mendling, 2006). The density metric is the ratio of the total number of arcs to the maximum number of arcs.

Following software engineering, these metrics are used to measure either comprehensibility or modifiability or both of them. Table 1 shows the usability of these metrics to measure either comprehensibility or modifiability as defined in the literature.

2.2 Work on Thresholds for Business Process Evaluation

Despite the importance of BP model to enterprises, there is a serious lack of an effective approach and

Table 1: Identified quality metrics for assessing comprehensibility and modifiability.

Quality metrics	Comprehensibility	Modifiability
CFC	$\star$	$\star$
HPC		$\star$
IC	$\star$	
NOA	$\star$	$\star$
NOAJS	$\star$	$\star$
CNC	$\star$	$\star$
CC	$\star$	
CP	$\star$	$\star$
D	$\star$	$\star$

$\star$: The metric is used to assess the comprehensibility or the modifiability.

support systems for BP models quality assessment (Sánchez-GonzáLez et al., 2013) and (Sadowska, 2015). Our literature review revealed that ISO standards for quality assessment and quality metrics are the basis of the different propositions. However, the common problem addressed by the existing works is the lack of thresholds for the defined quality metrics to be used during BP models quality assessment.

Makni et al. in (Makni et al., 2010) proposed a tool for evaluating the quality of BP models using existing complexity, coupling, and cohesion quality metrics. However, the authors did not focus on the identification of thresholds as the proposed tools ensure the evaluation based on thresholds introduced by the user for the different metrics.

In (Sánchez-González et al., 2010), the authors use the Bender method (Bender, 1999) to identify thresholds for some quality metrics. The method allows quantitative risk assessment in epidemiological studies based on the logistic regression model. This method has two major limitations: (i) logistic regression model requires a binary variable, and (ii) necessity to arbitrarily define $P0$ probability, which is used to calculate the Value of an Acceptable Risk Level (VARL). The Bender method was also used in (Sánchez-González et al., 2011), to define threshold for the CFC metric. In (Sánchez-González et al., 2012) the authors conducted an experiment to determine threshold values for gateway complexity metrics to be used for the evaluation of the understandability and modifiability of BP models. The authors also propose a Gateway Complexity Indicator (GCI) defined based on the identified threshold values for the selected gateway complexity measures.

Mendling et al. proposed an approach for predicting errors in BP model (Mendling et al., 2012). The approach is based on a set of quality metrics used in the literature for evaluating the quality of BP models. The author use logistic regression (Bender, 1999) and ROC curves (Hanley and McNeil, 1982) to determine thresholds for the used metrics.

In (Sadowska, 2015) Sadowska proposed a meta-model for assessing the quality of BPMN 2.0 process models. This meta-model is built upon the ISO/IEC 25010 standard (ISO, 2011). To evaluate the different quality characteristics, the author used a set of quality metrics defined in the literature. In addition, they used a BP repository of 57 BPs modeled with BPMN along with K-means to classify the possible values of quality metrics into 4 clusters. Based on the used quality metrics and the defined clusters the author proposed a system that supports the evaluation of BP models quality.

Our literature review revealed the lack of a consensus concerning thresholds values for BP models quality assessment. This is one of the important obstacles hindering the development of an effective system supporting qualitative assessment of BP models.

3 THRESHOLD DETERMINATION

We detail our approach for determining approximate thresholds for BP quality metrics in order to evaluate BP model quality in terms of modifiability and comprehensibility.

Our approach is based on data mining techniques; namely decision tree. Thus, four steps are required: data collection to build a repository of business processes, data preparation to create the learning and test datasets, data mining to build a decision tree, and validation to assess the performance of the resulted decision tree.

3.1 Data Collection

We created the "SOA-Based Business Process Database" by collecting a set of business processes that belong to different organizations to guarantee that our approach is generic (*e.g.,* academic institutions, commercial enterprises, healthcare centers, and banks). Furthermore, from each type of organization, we examined different business processes; for example, from academic institutions, we considered, among others, student registration, exam preparation, timetable creation, jury thesis defenses allocation, etc. All of these business processes are modeled using BPMN 2.0. The total number of the collected business processes is 1000.

After the model collection, we examined the processes in conjunction with design instructors from the

IT department of our university (considered as experts). The goal is to classify these processes according to the level of their comprehensibility and modifiability easiness. To this end, we organized ourselves into four groups. Each group examined 250 processes. Afterward, we conducted a cross-validation process among the different groups. Finally, we organized the business processes of the "SOA-Based Business Process Database" into three levels of comprehensibility (easy to understand, moderately difficult to understand, and difficult to understand) and three levels of modifiability (easy to modify, moderately difficult to modify, and difficult to modify).

3.2 Data Preparation

To prepare the data for the next phases, we built two matrices based on the database "SOA-Based Business Process Database". The first is devoted to the comprehensibility data, while the second is dedicated to the modifiability data. Each row in a matrix represents a BP from the "SOA-Based Business Process Database" and each column represents a quality metric among the identified quality metrics to measure comprehensibility and modifiability (*cf.* section 2.1). The last column of each matrix represents the level of comprehensibility (*i.e.,* easy to understand, moderately difficult to understand, or difficult to understand) or modifiability (easy to modify, moderately difficult to modify, or difficult to modify).

In our case, we used these matrices to create two sub-databases from each matrix: one for learning "training database" and one for testing "test database". The "training database" includes 70% of the "SOA-Based Business Process Database", and the "test database" comprises the rest.

3.3 Data Mining: Decision Trees

At this stage, we used decision trees to extract thresholds for quality metrics from the "SOA-Based Business Process Database". A decision tree consists of a root node and several intermediate and leave nodes. The transitions from the root node to a leaf node are based on the values of the criteria, quality metrics in our case. At each node, the criterion that maximizes the homogeneity of child nodes is chosen. Homogeneity of a node is reached when all the BPs of this node belong to the same class (*e.g.,* all the BP of a node are easy to understand, in the case of comprehensibility). A homogeneous node is usually a leaf node as it cannot be divided. A leaf node corresponds to the class, which is in our case the level of comprehensibility or the level of modifiability.

To create the required two decision trees (one for the comprehensibility and one for the modifiability), we used WEKA system, which is recognized as a landmark system in data mining and machine learning (Hall et al., 2009). WEKA supports several algorithms for the construction of decision trees like for example J48, ADTree, and REPTree. In this work, we first used all of the provided algorithms, and then we have chosen the best one (*i.e.*, the one that have a lower error rate) based on the validation stage (*cf.* subsection 3.4).

3.4 Validation

The literature proposes several possible ratios for assessing the quality of a prediction model. In our work, we use: precision (6), recall (7), f-measure (8), and global error rate (9). In the following, we discuss only the three best algorithms (based on the values of the used ratios), namely are J48, ADTree, and REPTree.

$$Precision = \frac{CorrectEntitiesFound}{TotalEntitiesFound} \quad (6)$$

$$Recall = \frac{CorrectEntitiesFound}{TotalCorrectEntities} \quad (7)$$

$$F-measure = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (8)$$

$$GlobalErrorRate = 1 - \frac{CorrectEntitiesFound}{TotalEntities} \quad (9)$$

3.4.1 Training Database based Validation

First, we calculate these ratios after testing the resulting decision trees (*i.e.,* comprehensibility and modifiability trees) on the training database. Table 2 and 3 show, respectively, the values of the different ratios for the three algorithms per decision tree. These tables depict that J48 algorithm gives the best values of precision, recall, F-mesure, and global error rates for both comprehensibility and modifiability.

Table 2 shows that we achieved very acceptable results with J48, for assessing the BP model comprehenisibility: the values of precision, recall, and F-measure are of 97.3% and the global error rate is of 2.7%. Similarly, Table 3 shows that J48 can also be used for assessing the modifiability of BP model as the values of precision, recall, and F-measure are of 96.1% while the global error rate is of 3.8%. However, to prove the effectiveness of the proposed decision trees, we need to use another database, "test database".

Table 2: J48 vs ADTree vs REPTree for decision tree of comprehensibility.

	J48	ADTree	REPTree
Precision	0.973	0.961	0.942
Recall	0.973	0.96	0.94
F-Measure	0.973	0.96	0.941
Global error rate	0.027	0.04	0.06

Table 3: J48 vs ADTree vs REPTree for decision tree of modifiability.

	J48	ADTree	REPTree
Precision	0.961	0.92	0.925
Recall	0.961	0.92	0.924
F-Measure	0.961	0.92	0.924
Global error rate	0.038	0.08	0.075

3.4.2 Test Database based Validation

To assess the performance of the proposed decision trees and choose the most suitable algorithm among those provided by WEKA, we evaluated the obtained trees using the "test database", which is extracted from the "SOA-Based Business Process Database". At this stage, we apply each decision tree to all BPs of the "test database" to assess the comprehensibility and modifiability levels of each process. This assessment is performed independently of the assessments already done by experts. The goal is to compare the experts' judgement with the obtained trees assessments and hence, to identify the error rate of our decision trees.

Table 4: J48 vs ADTree vs REPTree for decision tree of comprehensibility.

	J48	ADTree	REPTree
Precision	0.969	0.971	0.962
Recall	0.967	0.967	0.953
F-Measure	0.967	0.968	0.955
Global error rate	0.033	0.033	0.046

Table 5: J48 vs ADTree vs REPTree for decision tree of modifiability.

	J48	ADTree	REPTree
Precision	0.943	0.875	0.92
Recall	0.94	0.87	0.897
F-Measure	0.94	0.869	0.899
Global error rate	0.06	0.13	0.103

Tables 4 and 5 list the values of the four used ratios for evaluating the performance of the proposed comprehensibility and modifiability decision trees. These tables show that we achieved very acceptable results using the "test database" using J48. Indeed, the values of precision are: 96.9% for the comprehensibility tree and 94.3% for the modifiability tree. The values of recall and f-measure are 96.7% for the comprehensibility tree, and 94% for the modifiability tree. Finally, the global error rate is of 3.3% for the comprehensibility tree and 6% for the modifiability tree.

3.5 Discussion

Decision tree is used to classify the BP of the "SOA-Based Business Process Database" according to their level of comprehensibility (first decision tree) and modifiability (second decision tree) based on the values of the used quality metrics. Based on these decision trees, we defined a set of decision rules along with the thresholds of the different quality metrics for evaluating both comprehensibility and modifiability of a BP model. Tables 6 and 7, respectively, depict an extract of the defined decision rules for comprehensibility and modifiability.

Table 6: Excerpt of decision rules to assess the level of comprehensibility.

	Decision rules
R1	If $IC <= 12$ Then Easy to understand
R2	If $IC <= 17$ and $IC > 12$ and $CNC <= 1.26$ Then Easy to understand
R3	If $IC <= 17$ and $IC > 12$ and $CNC > 1.26$ and $CFC <= 3$ Then Moderately difficult to understand

Table 7: Excerpt of decision rules to assess the level of modifiability.

	Decision rules
R1	If $CFC <= 9$ and $HPC\_V <= 53$ and $NOA <= 6$ Then Easy to modify
R2	If $HPC\_V <= 53$ and $NOA > 6$ and $CFC <= 3$ and $NOA <= 12$ and $CP <= 0.077$ Then Easy to modify
R3	If $NOA <= 26$ and $CFC > 3$ and $NOA > 12$ and $HPC\_V <= 14$ Then Moderately difficult to modify

Table 8 shows the identified thresholds for each quality metric. However, the identified thresholds remain usually approximate and imprecise due to the fact that they depend on the expert judgments during the first phase, "data collection" (*cf.* subsection 3.1). In the next section, we detail the use of fuzzy logic to manage these approximate and imprecise thresholds.

Table 8: Obtained thresholds values of quality metrics.

Quality metrics	Comprehensibility	Modifiability
IC	$IC < 12$ $12 <= IC < 17$ $17 < IC <= 59$ $IC > 59$	-
CNC	$CNC <= 1.26$ $1.26 < CNC <= 1.65$ $CNC > 1.65$	$CNC <= 1.30$ $1.30 < CNC <= 1.54$ $1.54 < CNC <= 1.61$ $1.61 < CNC <= 1.85$ $CNC > 1.85$
CFC	$CFC <= 3$ $3 < CFC <= 9$ $9 < CFC <= 18$ $CFC > 18$	$CFC <= 3$ $3 < CFC <= 9$ $CFC > 9$
NOAJS	$NOAJS <= 39$ $39 < NOAJS <= 55$ $NOAJS > 55$	$NOAJS <= 7$ $7 < NOAJS <= 17$ $17 < NOAJS <= 33$ $33 < NOAJS <= 55$ $NOAJS > 55$
D	$D <= 0.043$ $D > 0.043$	$D <= 0.043$ $D > 0.043$
NOA	$NOA <= 14$ $14 < NOA <= 26$ $NOA > 26$	$NOA <= 6$ $6 < NOA <= 12$ $12 < NOA <= 26$ $26 < NOA <= 44$ $NOA > 44$
CP	$CP <= 0.031$ $CP > 0.031$	$CP <= 0.032$ $0.032 < CP <= 0.077$ $0.077 < CP <= 0.09$ $CP > 0.09$
HPC_V	-	$HPC\_V <= 14$ $14 < HPC\_V <= 53$ $HPC\_V > 53$
HPC_D	-	$HPC\_D <= 5.25$ $HPC\_D > 5.25$

4 FUZZY LOGIC FOR BUSINESS PROCESS QUALITY ASSESSMENT

According to his founder, fuzzy logic is a precise logic that supports imprecision and approximate reasoning (Zadeh, 2008). In this paper, we use fuzzy logic to manage the approximate and imprecise nature of the identified thresholds for the different quality metrics. Indeed, the use of fuzzy logic adjusts a bit the identified thresholds to be more general. This happens through the first step called fuzzification. At this step, the thresholds, which are crisp values, are transformed into linguistic values (*e.g.,* low, medium, high) known as fuzzy sets. The second step is the inference, which is based on a set of fuzzy rules. In our case, we deduce these fuzzy rules from the rules obtained in Section 3.5. Finally, the last step is the defuzzification, which produces a quantifiable (crisp value) result. In the remainder of this section, we detail the use of fuzzy logic to assess the quality of BP models

4.1 Fuzzification

Fuzzification converts crisp values of input variables (*i.e.,* quality metrics) into fuzzy sets (*i.e.,* linguistic values). This conversion is ensured thanks to a set of membership functions that we defined based on the identified approximate thresholds (*cf.* section 3.5). We defined one membership function for each possible fuzzy set per quality metric (*cf.* section 3.5).

In the first part of Fig.1 (*i.e.,* without fuzzification), *a* and *b* values represent the approximate thresholds determined through the use of decision trees and fuzzy sets associated with the different intervals fixed by experts (*i.e.,* low, moderate, and high). In this figure, each value of a quality metric can belong only to a single fuzzy set with a membership degree equals to 1. This case is true when the fixed thresholds are exact and precise. However, because it is not the case of the thresholds defined in this paper, we use the membership function depicted in the second part of Fig.1 (*i.e.,* with fuzzification). The values of *a'*, *a"*, *b'*, and *b"* are defined by experts for each quality metric. Each value within the intervals [a', a"] and [b', b"] belong to two fuzzy sets with different membership degrees. For example, the value "*x*" belongs to the two fuzzy sets "low" and "moderate" with membership degree of "*x1*" and "*x2*" respectively.

4.2 Inference

Inference is the second step in the decision making process using fuzzy logic. It is based on a set of fuzzy rules defined in a natural language. Fuzzy logic imposes that fuzzy rules are written according to a specific syntax "if X is A and/or Y is B then Z is C", where X and Y are input variables, Z is output variable, and A, B, C are their corresponding linguistic

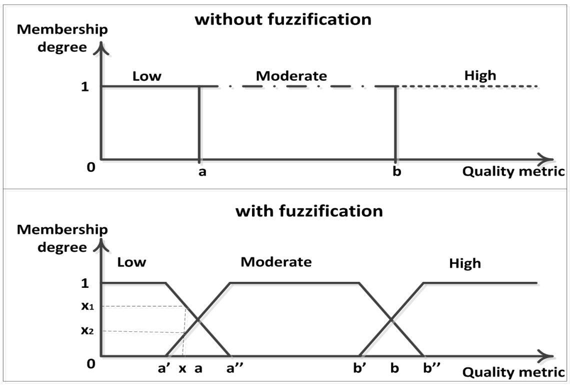

Figure 1: Membership function definition.

values. These rules are essential to any system built upon fuzzy logic as they are used to determine the values of the output variables based on the input values.

In our work, we defined rules to determine the level of comprehensibility and modifiability of a BP model based on the set of quality metrics. We used the set of rules obtained from the decision tree (*cf.* section 3.5): We replaced the crisp values with their corresponding linguistic values and rewrote the rules according to the syntax required by fuzzy logic. The total number of defined fuzzy rules is of 210 rules for the comprehensibility and 260 for the modifiability. Tables 9 and 10, respectively, depict an extract of the defined fuzzy decision rules for comprehensibility and modifiability.

4.3 Defuzzification

Defuzzification is the process which converts the fuzzy value of the output variable, obtained by the inference engine, into a crisp value. To do so, it aggregates the fuzzy outputs for all the activated rules to a one fuzzy set, which will be transformed into a crisp value.

In the literature, there are several defuzzification techniques like: center of gravity, center average, and maximum. We used the well-used defuzzification method: the center of gravity. The crisp value of the output variable is calculated using the following formula:

$$y* = \frac{\int_U y * \mu(y)\,\mathrm{d}y}{\int_U \mu(y)\,\mathrm{d}y} \tag{10}$$

where μ is the universe of discourse that considers all the output values according to the activated rules.

Defuzzification determines the level of comprehensibility or modifiability of a BP model as well as the degree of certainty of this level. For example, a BP model can be estimated as *easy to understand with a certainty degree of 70%*.

5 SYSTEM DEVELOPMENT: BP-FUZZQUAL

We developed a system; BP-FuzzQual, which supports our fuzzy-based approach for assessing the quality of BP models. It is developed in Java with Jdom and JFuzzyLogic libraries and under the Eclipse framework. The functional architecture of this system is shown in Fig.2. A complete video demonstrating the different steps of the BP quality assessment using our system is available at: https://youtu.be/qaCDjd–_54.

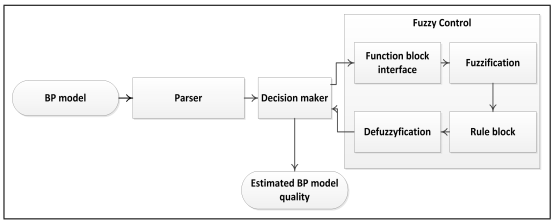

Figure 2: Functional architecture of BP-FuzzQual.

The following are the list of modules within BP-FuzzQual:

- Parser module: takes as input a BP model modeled in BPMN 2.0 and determines the crisp values of each used quality metric.
- Fuzzy Control module is implemented in Fuzzy Control Language (FCL) which follows the IEC1131 standard, the first international standard for process control software. FCL includes four components: function block interface, fuzzification, rule block, and defuzzification. FCL also allows defining a fifth optional component called optional parameters. The use of the four required components is detailed in the following:
  - Function block interface defines the set of input and output parameters as well as local variables, if required.
  - Fuzzification component defines a set of membership functions for each quality metric. Based on these membership functions, it converts the crisp values of the quality metric into linguistic values that will be used by the inference engine.
  - Rule block includes the set of linguistic rules that are used to estimate the quality of the BP model. These rules are defined following the syntax imposed by fuzzy logic.
  - Defuzzification component converts the linguistic value of the output variable “comprehensibility and modifiability levels” into crisp values. This conversation is based on a defined

Table 9: Excerpt of decision rules to assess the level of comprehensibility.

	Fuzzy decision rules
FR1	IF IC IS Low THEN ComprehensibilityLevel IS ComprehensibilityLevel IS EasyToUnderstand
FR2	IF IC IS Moderate AND CNC IS Low THEN ComprehensibilityLevel IS EasyToUnderstand
FR3	IF IC IS Moderate AND CNC IS Moderate AND CFC IS Low THEN ComprehensibilityLevel IS ModeratelyDifficultToUnderstand

Table 10: Excerpt of decision rules to assess the level of modifiability.

	Fuzzy decision rules
FR1	IF CFC IS Moderate AND HPC_V IS Moderate AND NOA IS VeryLow THEN ModifiabilityLevel IS EasyToModify
FR2	IF HPC_V IS Moderate AND NOA IS VeryLow AND CFC IS Low AND CP IS Moderate THEN ModifiabilityLevel IS EasyToModify
FR3	IF HPC_V IS High AND CFC IS Low AND NOA IS Low AND CP IS Moderate THEN ModifiabilityLevel IS ModeratelyDifficultToModify

technique (*e.g.,* center of gravity, center average, and maximum). As per section 4.3 the proposed system uses the center of gravity technique.

- Decision maker module runs the FCL code in order to estimate the quality of the BP model. This module takes as input the crisp values produced by the parser module and communicates these values to the fuzzy control module. The decision maker module is developed using java language.

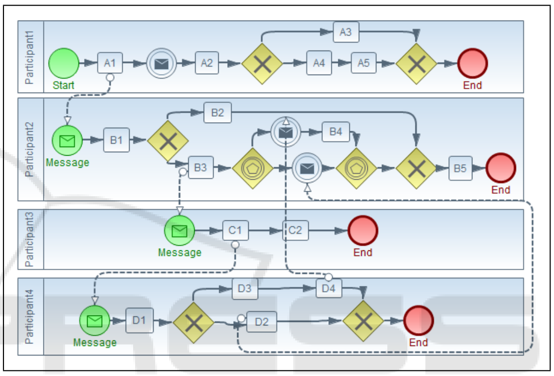

Figure 3: Example of BP model modeled with BPMN.

6 EXPERIMENTS

For validating the approach and the system, we carried out two types of experiments. The first was done using our system, BP-FuzzQual, and the second involved anonymous students from our college. In both experiments the business process model of Fig. 3 was used. In this model, we use abstract labels in tasks and pools in order to bypass the complexity that could be caused by the business domain.

Experiment 1: consists of modeling a BP using BPMN2 modeler, for example. Then if the BP engineer selects "Quality assessment" menu and then "Assess BP model comprehensibility", the system displays the crisp and fuzzy values of the different quality metrics used for assessing comprehensibility. It also displays the estimated level of comprehensibility. For instance, the estimated comprehensibility level of the BP model of Fig. 3 is *"Moderately difficult to understand with a certainty degree of 63%"*. Fig. 4 shows the interface for comprehensibility assessment.

In addition, if the BP engineer selects "Quality assessment" menu and then "Assess BP model modifiability", the system displays the crisp and fuzzy values of the different quality metrics used for assessing modifiability. It also displays the estimated level of modifiability. For instance, the estimated modifiability level of the BP model of Fig. 3 is "Moderately difficult to modify with a certainty degree of 100%". Fig. 5 shows the interface dedicated for modifiability assessment.

Experiment 2: uses the BP model of Fig. 3 and two sets of exercises (available at: https://sites.google.com/site/bposcteam2015/ressources). In the first exercise, 60 undergraduate students from our College were asked some multi-choice questions to assess their understanding of the BP model. In the second exercise, the same students were invited to make some changes in the BP model. Fig. 6 represents the number of correct and incorrect answers for the first exercise. In this figure, 78% of the responses are correct showing that the majority of students understood the BP model. This is also confirmed through their responses to the last question of the first exercise, which is about their ability to understand the BP model. Indeed, as depicted in Fig. 7 76% of students considered the BP model as moderately difficult to understand, 14% as easy to under-

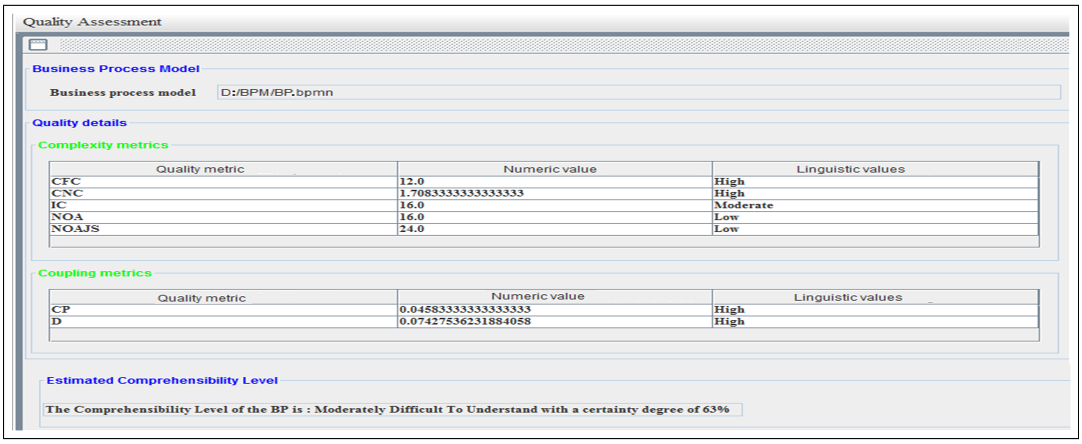

Figure 4: Comprehensibility assessment interface.

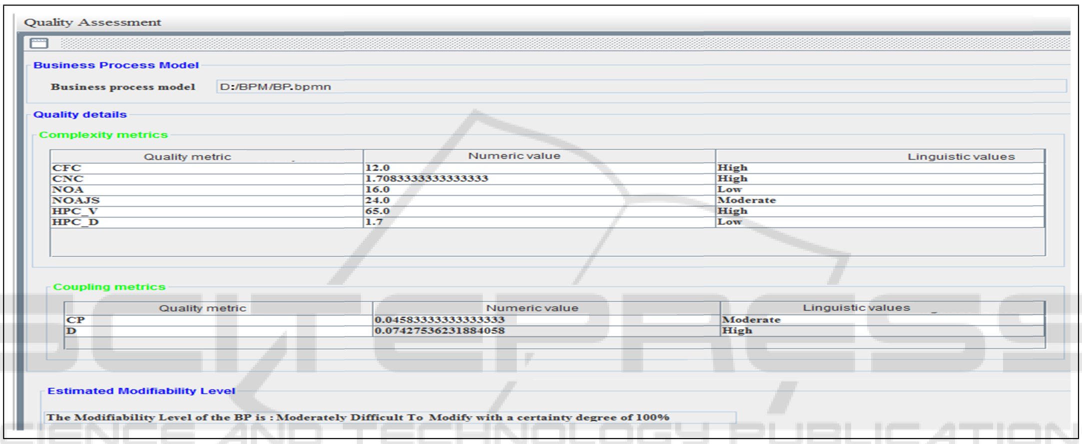

Figure 5: Modifiability assessment interface.

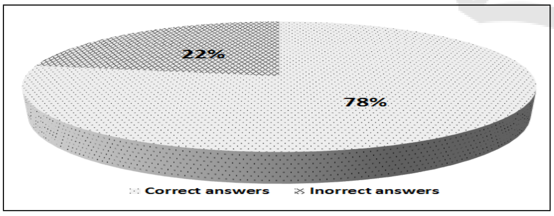

Figure 6: Correct and incorrect answers for comprehensibility assessment.

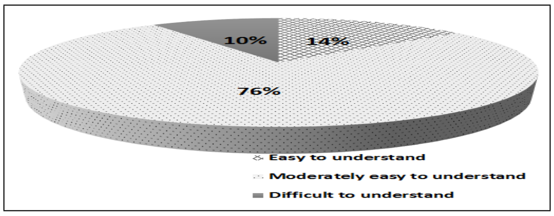

Figure 7: Students' judgments about the BP model comprehensibility level.

stand, and 10% as difficult to understand.

Fig. 8 represents the number of correct and incorrect answers for the second exercise. In this figure, 69% of the responses are correct showing that a good number of students have correctly modified the BP model. In addition, as depicted in Fig. 9 53% of students considered the BP model as moderately difficult to modify, 33% as difficult to modify, and 14% as easy to modify.

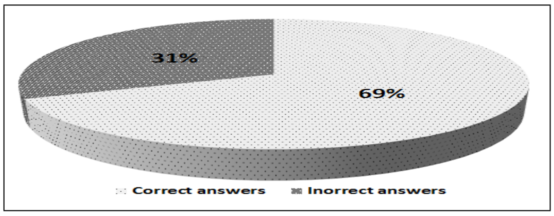

Figure 8: Correct and incorrect answers for modifiability assessment.

To sum up, the experiment shows that the students considered the BP model as moderately difficult to understand; this is proved by their responses to the comprehensibility questions. This is in line with the

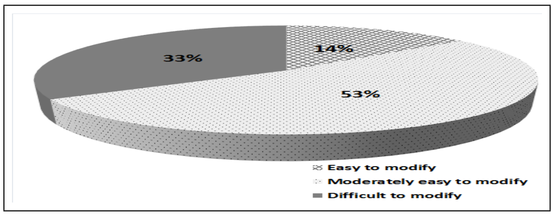

Figure 9: Students judgment about the BP model modifiability level.

evaluation done by FuzzQual, which considers the BP model as moderately difficult to understand. Similarly, when dealing with modifiability, the students consider the BP model as around moderately difficult to modify and difficult to modify while FuzzQual considers that the BP model is moderately difficult to modify. Overall, these comforming results show that our approach produces encouraging results that should be proved through additional experiments.

7 CONCLUSION

BP modeling is important for enterprises that wish to remain competitive. However, this task, which is usual manual, can result into a BP model of a poor quality. Such a model could affect the remainder BP lifecycle phases (Weske, 2010). To overcome this challenge, Mendling et al. proposed seven guidelines that can assist BP engineers develop a BP model of a high quality (Mendling et al., 2010). Other research initiatives focus on the use of quality metrics used in the field of software engineering to assess the quality of BP models (Vanderfeesten et al., 2007b), (Mendling et al., 2012), and (de Oca et al., 2015). However, to date, there is no consistent framework for assessing BP models quality. The lack of such a framework is due to different challenges like the lack consensus about the used metrics, their thresholds, etc.

To tackle these challenges, we proposed, in this paper, a fuzzy-based approach for assessing the quality of BP models modeled in BPMN 2.0 in terms of comprehensibility and modifiability. The proposed approach is based on the ISO/IEC 25010 standard as along with a set of quality metrics used in the literature to assess BP models quality. It consists of two essential phases: threshold determination and fuzzy logic application. The first phase applies data mining techniques, specifically decision tree, to determine approximate thresholds for each used quality metric to assess the quality of BP models, modeled using BPMN language, in terms of comprehensibility or modifiability. This phase used the "SOA-based Business Process Database", which is built within our laboratory. The second phase of the proposed approach uses the approximate thresholds identified in the first phase along with fuzzy logic (Zadeh, 1965) to assess the quality of BP models. The use of fuzzy logic aims at dealing with the approximate and imprecise nature of the obtained thresholds. To automate BP models quality assessment we developed FuzzQual, which is a system supporting the proposed approach. This system is developed in Java language and under eclipse framework. To prove the performance of the proposed system, we conduct two types of experiments. The former is done through the proposed system while the second is accomplished in conjunction with students from our college. These preliminary experimental evaluations of the proposed system show encouraging results.

As a future endeavor, we plan to validate the proposed fuzzy approach for BP quality assessment through some real case studies and in conjunction with enterprises' experts. In addition, we plan to assess the quality of BP models in terms of other quality characteristics among those presented in the ISO/IEC 25010 quality model. We, also, intent to put in place an approach and its support system that could help enterprises improve the quality of their BPs.

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