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A Decision Support System for Project Risk Management based on Ontology Learning

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Abstract: Project Risk Management (PRM) is one of the main concerns of project management executives and professionals. Although PRM frameworks and risk models are mature enough to provide a systematic approach for managing risks, these practices remain ad hoc and non-standardized. In addition, there is no significant work shift toward PRM recommendation systems through inference rules and axioms. This study aims to bridge the cited gaps in PRM by developing a decision support framework based on an ontology that predicts personalized recommendations for managing PR processes effectively, and then making the right decisions. To this end, this framework takes advantage of the ontology semantic strengths to model a unified PRM knowledge relying on PMI's framework. The idea is to parse PMI's standard for PRM to enrich and exploit an existing PR Ontology. The enrichment process is driven by the Ontology learning (OL) tasks using Natural Language Processing techniques (NLP) to extract the main concepts, properties as well as OWL DL axioms and SWRL rules. Then, through Jena_rule engine, this decision system infers recommendations, by which a team member asks for a specific targeted risk-related request. Based on this approach, a decision system is developed to illustrate the assets of ontological reasoning and thereby the reliability of decision support. The potential benefits of the proposed framework are evaluated using a questionnaire survey that proves the overall positive evaluation.

Keywords: Ontology learning, decision support system, Knowledge retrieval, SWRL Rule, NLP, PMI's Standard for Project Risk Management.

I. Introduction

The difficulty to make concerned decisions related to PRM increases project complexity and even its failure. PRM remains one of the major concerns of executives and professionals involved within projects. PRM specialists are trying to better study the potential impacts of their decisions and assess the risks as precisely as possible [1]. Refer to PMBOK Guide [2], PRM is a systematic process focusing on conducting RM planning, identification, analysis, responses, and monitoring and control on a project, where five main Processes are defined:

1. RM Planning: focusing on developing the overall RM plan which defines how PR process will be

executed.

2. Risks Identification: focusing on identifying all the knowable risks and documenting their characteristics.
3. Risk Analysis: focusing on evaluating the key risk characteristics to be prioritized for further analysis.
4. Plan Risk Responses: focusing on developing response strategies for the individual risks and for the overall project risk.
5. Risks Monitoring and Control: focusing on evaluating the efficiency of PRM.

Literature review shows that this domain presents benefits when it is developed according to standards, audits and regulations to make openly decisions without bias [3]. Although PRM frameworks and risk models are enough mature to provide a systematic approach for managing PR, authors [4]-[5]-[6] pointed out the lack of a shared common vocabulary that implies incomplete understanding of PRs, an ambiguous interpretation of their contents as well as an inconsistent knowledge sharing of risk-related concepts. Hence, ontology, as one of the main cornerstones of representing the knowledge in a meaningful way [7], play a key role in modeling terms/ concepts hidden in texts and makes it human and computer understandable. More precisely, ontological approach is the means to structurally represent an agreed-upon asserted knowledge interpreted and reused by humans or machines, and then infer new knowledge through its reasoning capability.

Formally, Ontology "O" is a quadruple $O = (C, P, I, A)$ where C a set of Concepts within a domain, P a set of properties (relationships of those concepts), which includes Two subsets: P_b is the builtin properties, such as `rdfs:domain` and `rdfs:range` and P_u is the user-defined properties, where $P = P_b \cup P_u$. I a set of instances associated with the set of concepts C and properties P, and A a set of formal Axioms (illustrate and constrain the concept behaviours) [8].

Since manually ontology construction is time-consuming, resource-intensive and costly process, OL process attempts to (semi-) automatically retrieve and represent the knowledge from text in machine-understandable form using one of the primary ontology languages, namely, Resource Description

Framework (RDF), Resource Description Framework Schema (RDFS), Web Ontology Language (OWL). This process is supported by semi-automatic tools and NLP techniques. These techniques parse a formal representation and a meaning of a text written in the form of natural language which can be exploited then for the reasoning and inferring tasks [7]-[8].

When considering the application and studies of ontology related to PRM, it's worth noting that there are a number of ontological approaches that have been developed [9]-[10]-[11]-[12] and have proved the potential benefits of ontology related to this domain; from which, three main items can be deduced (i) most of these ontologies does not address the overall PR process whereas their scope is limited to risk analysis and assessment processes, (ii) none of them focus to conceptualize PRM knowledge with respect to standards and best practices by applying the OL process, (iii) rather than a conceptual framework, ontology provides powerful querying and reasoning mechanisms successfully exploited by Decision Support System (DSS); whilst, ontology and DSS are handled separately in the PRM and even the examples of PR Ontology-Based DSS are quite limited.

With respect to these gaps, we propose to develop an Ontology-Based Decision Support System for PRM domain that provide the project team clear guidelines to effectively manage risks, and then make decisions based on the right recommendations. To this end, we address the problem of OL that could be applied to text analysis as a way to enrich an existing ontology which will be integrated further in a decision support framework. Thus, "PRM-Ontology" [13], an owl ontology covering PRM knowledge, will be extended with the retrieved candidate elements from a given text, since it's founded very close to our scope. This ontology will be learnt from an unstructured corpus which is the "PMI's standard for PRM" [14] as a reference guideline that embodies a set of knowledge and recommendations used by PM professionals and domain experts, as justified below:

- PMI's standard for PRM is globally applicable and consistently applied with defined Tools & Techniques (T&T) and detailed artifacts for each process.
- PMI practice standard describes processes, activities, inputs, and outputs for a specific knowledge area.
- PMI is incorporated in the ISO/PC236 and ISO/TC258; so PMI's PRM standard is closely aligned with ISO.

Therefore, the purpose of this paper is twofold. Firstly, we will convert the knowledge and recommendations text from PMI's standard into concepts, properties and reasoning rules respectively. This step will be driven by OL process using the NLP techniques. Then, we integrate the extracted elements to enrich the existing PRM-Ontology. Secondly, the enriched ontology model together with the obtained semantic rules constitutes the knowledge base of our decision support framework, which can be interpreted by an inference engine to provide automatic knowledge-based solutions. To do so, through Jena inference engine, this framework infers personalized recommendations, by which a team member ask for risk-related request more targeted. In this way, for each PR process, the related T&T and the artifacts can be captured and inferred semantically according to a team member's request. A real case is implemented illustrating the feasibility and effectiveness of the proposed DSS.

The rest of this paper is structured as follows. The section2

reviews related studies about Ontology-based DSS in PRM along with a comparative analysis. A detailed description of the proposed decision system, its architecture and phases are presented in section3. The system specification and implementation case are illustrated in Section 4. Section 5 elaborates a survey questionnaire that reveals the potential benefits of the proposed DSS. Lastly, in Section 6, we conclude with some future work.

II. Literature review

In this section, we discuss the previous studies and findings related to decision support system for PRM based on ontological model. When considering the application and studies of DSS based on ontology model for PRM, many efforts have already been devoted especially for construction project.

One of the first work has been undertaken in [15] is to develop an Ontology-based RM (ORM) framework that enhances the RM workflow performance and the knowledge reuse during the project life cycle. The project risk ontology is designed to conduct the knowledge extraction process. In [16], a knowledge-based risk mapping tool is proposed to assess risk-related variables that may conduct to cost overrun. To this purpose, the ontology reported in [6] has been reused to assess risk-related variables that may lead to cost overrun. A risk-vulnerability assessment methodology is used to predict the possible risk paths and their impact on cost. Also, a lesson learned database has been included to be reused for forthcoming projects. In this line, Ding et al [17] established an ontology-based framework for the construction and reuse of risk knowledge in the BIM (Building Information Modeling) environment, using semantic network and semantic retrieval mechanism, in an effort to improve the risk analysis process. For that aim, the risk knowledge is formalized by means of an ontology-based semantic network from which the interactions between risks, risk paths can be inferred by a risk map. Jiang et al [18] proposed an ontology-based safety risk CBR method by combining ontology and CBR (case-based reasoning) for construction safety risk management in order to provide a decision making framework for managers to implement safety risk identification and assessment. For that aim, construction safety risk ontology is modeled to structuralize all the safety risk knowledge. Then, an improved algorithm combining similarity and correlation is implemented to search similarity and correlation of cases. The study presented by Filippetto et al [19] put forward a risk prediction model for software project management based on project risk ontology to assist teams identifying and monitoring risks at different phases during the project life cycle. Also, the proposed model infers recommendations considering the characteristics of each new project. In [20], Dhakal et al implemented a semantic knowledge-based decision support system that supports the classification, retrieval, recommendation, of knowledge on DRCPs (Disaster-Resilient Construction Practices) through three modules respectively: (1) document classification module to annotate documents with concepts from an ontology-based semantic model, (2) document retrieval module to retrieve the relevant documents based on users' queries and (3) document recommendation module to recommend documents to users based on their search history,

profiles, locations and preferences. The presented ontology is for formally representing and reasoning over the knowledge of DRCPs.

A comparative analysis of the related studies according to the following criteria is presented in Table 1.

Reference	PR process	OL & NLP	Axioms & Rules
[15]	Identification/Analysis/responses	X	X
[16]	Identification/ assessment	X	X
[17]	Analysis	X	✓
[18]	Identification/assessment	X	X
[19]	Analysis/responses	X	X
[20]	Assessment	✓	✓

Table 1. The related studies: comparison.

Table 1 show that ontology has been well integrated into DSS for structurally representing an agreed-upon PRM terminology rather than for reasoning purposes using rules and axioms. These works have considered only the knowledge related to construction project. However, the application of Ontology-Based DSS in a generic way to improve its reusability for other specific project was not yet implemented. Even, most of these works have mainly focused on risk identification and risk analysis rather than decision making. Moreover, smart technologies are also in need of further examination since these works have presented manually ontology building process from scratch without considering the OL process using semi-automatic tools or NLP techniques.

To this end, this paper intends to combine and extend the previous studies in several ways. The knowledge retrieval process is done automatically using NLP techniques with respect to OL layer cake to comply with PMI's standard for PRM. The preprocessing tasks put emphasis on converting the corpus into OWL axioms to extract new concepts and relationships (taxonomic/ semantic), as well as on the automatic extraction of reasoning rules and axioms. Then, the retrieved knowledge will be integrated into the PRM-Ontology through the enrichment process to be exploited further in the inference tasks through a decision support framework. Thus, the proposed decision system predicts targeted recommendations, at each PR process; the related T&T and the artifacts are captured and inferred with respect to a team member request.

III. The proposed decision support framework for PRM

The DSS proposed herein, in conjunction with ontology, aims to cover the whole decision making process from structuring and integrating of PRM knowledge, to inference new knowledge, and it is capable of encoding (i) the team member 'request, (ii) the relevant data for it and (iii) the recommendations produced for such request through a rule-based reasoning mechanism, capable of directing each PR process with its corresponding T&T and artifacts. The overall framework relies on three main modules: (1) the Knowledge Base (KB), (2) the rule-based engine and (3) the user interface as shown in Figure 1.

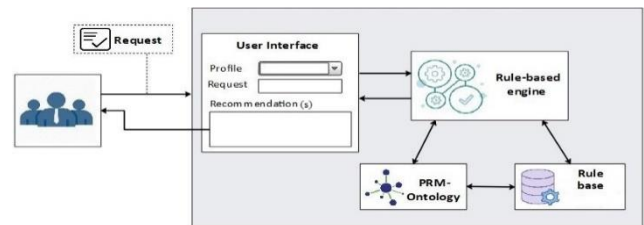


Figure 1. The overall system architecture

The workflow of this decision system is summarized into four steps as follow:

1. The PRM-knowledge are automatically extracted for PMI practice standard for PRM via NLP techniques, and then explicitly formalized with respect to OL layer cake to enrich an initial PRM-Ontology. The enrichment process does not treat only OWL concepts and properties but also SWRL (Semantic Web Rule Language) rules are inferred and stored into a Rule Base (RB).
2. A team member interacts through the user interface to select its profile (e.g., risk manager, risk owner, risk action owner, project manager, etc) and then to request any recommendation for a specific process/case.
3. Once this request and profile are received, through its rule-based engine, the system generates a set of inference rules. Thus, the rule-based engine serves as a bridge which links the PRM-Ontology and the SWRL rules to infer recommendations for a targeted request. Likewise, PRM-Ontology feed the rule-based engine with the relevant domain concepts and their associated relations so as to allow the engine combine rules with concept instances while inferring. Thus, our knowledge Base (KB) has two main components: PRM-Ontology (.OWL file) and the SWRL rule base (.Rule file).
4. The system displays the user the corresponding recommendations which are expressed in natural language. Thus, a project team can make decision easily and efficiently supported by PMI reference.

For that aim, two main phases are developed: knowledge base construction phase and rule-based reasoning phase. A detailed description of each phase along with its main contribution is provided in the following subsections.

A. The knowledge base construction based on ontology enrichment process

This phase presents the construction of the system's model that is represented by the PRM domain ontology and the formalized rules in the form of *If-Then* statements. Thus, as mentioned in our previous work [21], automated ontology enrichment supported by PMI's standard for PRM is adopted (described in Figure 2).

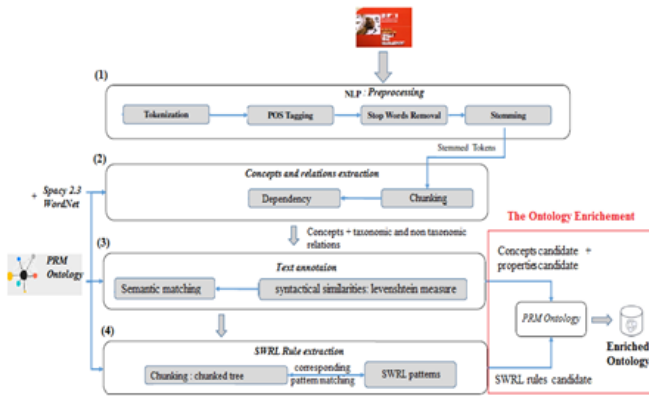


Figure 2. An overview of our approach based on OL process

The ontology enrichment (Figure 2) is the process for extending an existing ontology with new concepts, properties, axioms and rules, through adding or modifying an initial ontology guided by OL sub-tasks where the corresponding terms and synonyms are converted to the form of concepts. Then the taxonomic and non-taxonomic relationships among these concepts are automatically founded. Finally, axiom patterns are instantiated and general axioms are discovered from unstructured text. This whole process is called the ontology learning layer cake [22]. So as, we have adopted the following four steps:

1) Text pre-processing

Is to prepare the unstructured text for the semantic annotation task using NLP techniques through which we work out the grammatical structure of sentences and preceded the tokenization, stop words removal, part-of-speech tagging (POS), and stemming tasks [23]. Algorithm1 presents the pseudo code of pre-processing task: (1) Tokenization is the task that splits a character sequence up into (words/phrases) called tokens (line3). (2) part-of-speech tagging is that assign for each token its related part-of-speech [noun (NN), verb (VB), Determiner (DT)] etc. So, we tag each word by its corresponding nature using the pos-tag () function (line 4). (3) Whereas stop words removal is to remove some stop words from the text which have no significant relevance (adjective ADJ or adverb ADV) (line 5); While stemming is the task of removing word to the stem (root) of derived words (line5).

Algorithm1: text Pre-processing

1. Input: Corpus C
2. Outputs: stemmed tokens
3. Sentences: Segmentations in {C}
Tokens: for each token in sentences
4. Tagged part Of Speech: perform part of speech tagging for each token in sentences
5. For each token in sentence perform stemming if token is not in Stop Word (ADJ, ADV)

A recommendation sentence from our PMI's standard is as below:

"once risk identification, Risk Owner must evaluate the importance of each risk to prioritize the individual risks and evaluate the level of overall project risk, and then determine the appropriate responses using qualitative techniques to address individual risks, using quantitative techniques for the overall effect of risk" [14]. The result of the pre-processing

algorithm1 is:

```
[ 'once' / IN, 'risk' / NN, 'identification' / NN,
', 'Risk' / NN, 'Owner' / NN, 'must' / VBZ,
'evaluate' / VBZ, 'the' / DT, 'importance' / NN, 'of' / IN,
'each' / NN, 'risk' / NN, 'to' / DT, 'prioritize' / VBZ,
'the' / DT, 'individual' / NN, 'risks' / NN, 'and' / DT,
'evaluate' / VBZ, 'the' / DT, 'level' / NN, 'of' / IN,
'overall' / NN, 'project' / NN
', 'risk' / NN, ', , , , 'and' / DT, 'then' / IN,
'determine' / VBZ, 'the' / DT, 'responses' / NN,
'using' / VBG, 'qualitative' / NN, 'techniques' / NN,
'to' / IN, 'address' / VBZ, 'risks' / NN,
', 'using' / VBG, 'quantitative'
/ NN, 'techniques' / NN, 'for' / DT, 'the' / DT, '
```

2) Term/Concept Extraction and relation discovery

Several approaches use linguistic methods for extracting terms and concepts. Refer to [24], the basic techniques for entities extraction are part-of-speech (POS) tagging and chunking task which segments and labels multi-token sequences (Algorithm 2). This step is assisted by word Net [25] and spacy3.2 vocabularies [26].

Algorithm 2: Concepts and Properties discovery

1. Input: stemmed tokens, POS Tagge
 2. Output: concept List, properties List
- Begin
Read the stemmed tokens as array:
For each word in stemmed tokens **do**:
Gets the word Tag by POS Tagger ():
if word Tag is NN or its subsequent then
Add word to concept List;
else if word Tag is VB or its subsequent
then Add word to properties List;
Else ignore the current word;
End

Through Spacy Rule Based Matching [27], the taxonomic and non-taxonomic relations among those concepts are defined using two patterns "subject-Is a- Object" and "subject-predicate-subject" respectively. As well, "subject-such as-Object" pattern is created to find the instances associated to each concept. Algorithm3 shows the pseudo code of rule based matching.

Algorithm3: Rule based matching

- ```
//initialize spacy matcher
1. matcher = Matcher (nlp. vocab)
2. Pattern= Define pattern matching two concepts
//Add the defined Pattern to the matcher
3. matcher. Add (id pattern, Pattern)
//use the matcher on the corpus C
4. matches= matcher(C)
```

Finally, to determine the relevant terms in our corpus, TF-IDF (Term Frequency and Inverse Document Frequency) measure is computed using TfidfVectorizer [28]. This measure calculates the frequency of occurrence of each term x within a document y, using the following formula:

$$(TF - IDF)_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right) \quad (1)$$

Where:

$tf_{x,y}$ : frequency of x in y

$df_x$ : number of documents including x

N: total number of documents

Thus, the words with high TF-IDF score are considered based on TF-IDF results as below:

Number of features : 1550  
Most common words in our corpus :

|            | TF-IDF Score |
|------------|--------------|
| project    | 0.569533     |
| activity   | 0.271549     |
| schedule   | 0.261937     |
| cost       | 0.230096     |
| management | 0.228294     |
| process    | 0.191046     |
| plan       | 0.187441     |

Least common words in our corpus :

|               | TF-IDF Score |
|---------------|--------------|
| involvement   | 0.000601     |
| iso           | 0.000601     |
| isolate       | 0.000601     |
| jad           | 0.000601     |
| justification | 0.000601     |
| keep          | 0.000601     |
| joint         | 0.000601     |

### 3) Semantic annotation

After the concept/term extraction as well as their relationships, we focus on whether each extracted token will be a candidate concept or a candidate property for extending the initial PRM Ontology or not. Thus, in order to match each token to the content of the PRM ontology, Levenshtein measure [29] is computed to search the syntactical similarity. Then, we apply the semantic matching to find the synonyms relations with Word Net:

```
def syns(s):
 l = []
 for w in nlp(s):
 syn = wordnet.synsets(w.text)
 a = w.text
 if len(syn) > 0 and w.pos_ in ['NN', 'VB']:
 a = syn[0].name().split('.')[0]
 l.append(a)
 return l
```

```
df["Sentence"] = df["Sentence"].apply(lambda s : " ".join(syns(s)))
```

The main change in the ontology enrichment process is adding new concepts in the initial ontology as presented below:

AddClass (C1, PRM Ontology)  
Input: C1 (candidate concept in the form “NN”), PRM Ontology

**Case 1:**  
If C1 not exist in PRM Ontology, **Then:**  
Find similarity among C1 and PRM concepts: **Levenshtein measure** is used.  
If we find similarity value:  $sim [C1] = C_i$  //The lower distance is the more similar terms  
**Then** add semantic relation Is Similar (C1) =  $C_i$

**Case 2:**  
If C1 no exist in PRM Ontology and no similarity obtained with its concepts  
**Then** AddClass (C1, PRM Ontology)

### 4) SWRL Rule Construction

The evolution of the PRM ontology will be achieved by OWL changes (add Concept, Add Object properties, data properties, etc ) as well as SWRL changes (SWRL Built In, SWRL Expression, addAtom, addClassAtom, etc) extracted from our pre-processed corpus.

Thus, besides the knowledge explicitly defined in the PRM Ontology using RDF/OWL, our purpose is to convert the PMI’s standard recommendations into inference rules, in particular into SWRL rules for its compatibility with OWL DL ontology. In SWRL, rules are described as an implication between an antecedent (body) conjunction and a consequent (head) conjunction in the following form [24]:

$$a_1 \wedge a_2 \dots \wedge a_n \rightarrow c_1 \wedge c_2 \dots \wedge c_n \quad (2)$$

Where  $a_1, a_2, \dots, a_n$  are atomic formulas describing conditions and  $c_1, c_2, \dots, c_n$  is the obtained result when conditions are satisfied. Both parts are expressed in terms of OWL classes, properties, individuals and data values defined in that ontology.

Obviously, these extracted SWRL rules are stored in a separate rule base (.Rule file) which is associated with the PRM-Ontology as shown in Figure 1. To this purpose, a set of patterns are firstly defined from [30] to classify the set of rules of our corpus. Thus, a candidate rule will be matched to those defined patterns for identifying its corresponding builder patterns.

Then, to parse these recommendations, we chunk them for generating further the chunked tree of each recommendation:

```
import nltk
import spacy
nlp = spacy.load('en')
doc = nlp(sentence)
tokens = [(d.text, d.pos_) for d in doc]
cp = nltk.RegexpParser(grammar)
tree = cp.parse(tokens)
if draw_tree:
 tree.draw()
return tree
```

Further, for each recommendation formalized by its chunked tree, we search its related entities in the PRM ontology (concept, instance, property, or literal). After generating for each recommendation its chunked tree (rule candidate) and their corresponding matching with the PRM Ontology, we converted it into SWRL rule according to the defined SWRL patterns (Figure 3).

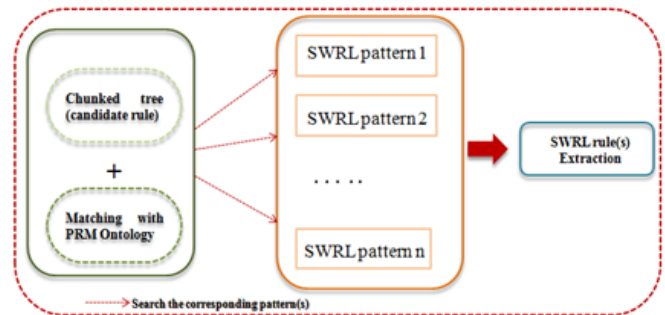


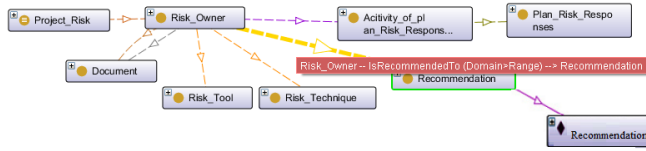
Figure 3. SWRL rule extraction process [21]

To illustrate how rules are codified, a reasoning sentence to infer the steps followed when a known Project Risk “PR” is allocated to a Risk Owner “x” in order to plan strategies and

actions by showing the required artifacts and the corresponding T&T, can be expressed in SWRL notation (Rule\_1) as follow:

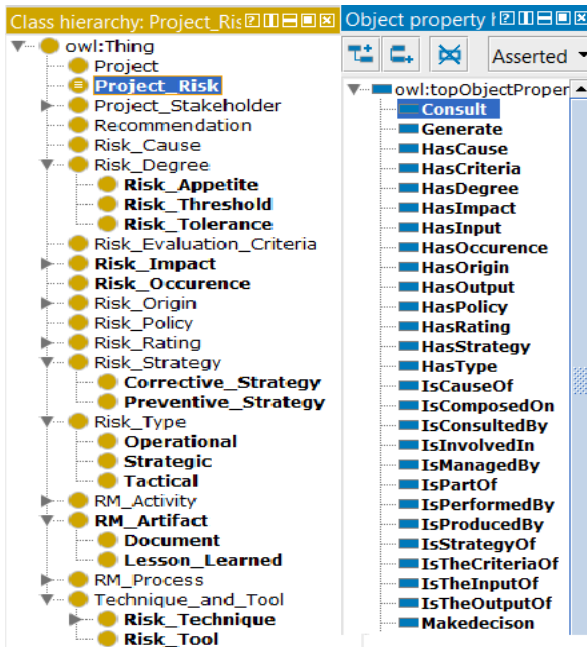
```
ProjectRisk(?PR) ^ (Is AllocatedTo max 1 RiskOwner)(?x) ^
Consult (? x, RMPlan) ^ Document (RMPlan) ^ Consult (? x,
RiskRegister) ^ Document (RiskRegister) Consult(? x, ?L1) ^
lesson_Learned (?L1) ^ IsRecommendedTo(? x, Recommendation5)
Recommendation(?Recommendation5) ^ NeedTheUseOfTool (?x,
DecisionSupportTool) ^ RiskTool (DecisionSupportTool)
→ Perform(? x, ?P4) ^ Update(risk Log)
```

These following steps co-result, in the rule \_1 consequent, to perform successfully RM\_Process (?P4) by the RiskOwner (?x) and then update the RiskRegister. After executing the preceding of rule\_1, the risk owner could directly find out the appropriate recommendations to plan strategies and actions in a correct manner as depicted in Figure 4 that represents the antecedent of rule\_1 in RDF/OWL fragment.



**Figure 4.** The antecedent of the extracted SWRL rule using Onto Graf [21]

Finally, once the retrieval process based on OL tasks, we have updated the initial PRM Ontology by adding the candidate concepts and properties as well as alimenting the rule base by the candidate SWRL rules. Figure 5 presents an excerpt of the new enriched ontology.



**Figure 5.** An excerpt of the enriched ontology based on ontology enrichment

As a result, we obtain a KB including 1492 concepts, 360 object properties, 66 instances, 90 data properties, 187 axioms and 21 SWRL rules, counted from ontology metrics view of protégé 5.5.

In order to evaluate the coverage of the extended PRM

Ontology of the PMI' Corpus (C), we computes the following information retrieval measures [31] (see Table 2):

- Precision: the percentage of Ontology concepts (O) that overlap with the (C):

$$\frac{|O \cap C|}{|O|} \quad (3)$$

- Recall: the percentage of the Corpus terms (C) that overlap with the (O):

$$\frac{|O \cap C|}{|C|} \quad (4)$$

- F-Measure: the harmonic mean that combines both the values of precision and recall.

$$F - \text{Measure} = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}} \quad (5)$$

|   | O    | C    | O ∩ C | Precision | Recall | F-Measure |
|---|------|------|-------|-----------|--------|-----------|
| 1 | 783  | 1836 | 659   | 0.841     | 0.358  | 0.52      |
| 2 | 1492 | 1836 | 1229  | 0.82      | 0.67   | 0.74      |

*Table 2.* The enriched ontology vs. the initial one for the same corpus.

Table 2 results prove that the enriched ontology (2) fits well with the PMI's standard for PRM compared to the initial one (1) [14] in term of coverage criterion, where:

- The overlapping terms (1229) presents 67% of the concepts covered from our Corpus. However, the initial one presents only 35.6%.
- The enriched ontology (2) presents a precision score of 0.82, a recall score of 0.67. Hence, we achieved an average result of F-measure of 0.74. Knowing that F-score attains its best at 1 and its worst value at 0. So, the new ontology presents the higher coverage rate that the initial one (with F-measure 0.52).

### B. The Rule-based reasoning phase

This phase represents the reasoning strategy of our decision system based on the developed KB. It is supported by Jena reasoning engine which applies the rules with the data (asserted facts) stored in the KB to reason and infer new facts. When the data matches the rules conditions, the engine modifies the KB (fact assertion or retraction, or to execute functions) and then shows the inferred facts. There are two main reasoning strategies namely forward chaining and backward chaining [32]. Yet, the forward chaining strategy starts from existing facts and applies rules to derive all possible facts; while backward chaining starts with the desired conclusion and applies backward chaining to search supporting facts. The user application interacts with inference engine via APIs (Jena inference API in our case) that support reasoning strategies, storing facts, querying the result data, etc.

In this work, we define a reasoning process based on the forward chaining strategy. As presented in Figure 6, rules are applied to the asserted facts, and the entailed statements are immediately added to the KB until it reaches the conclusion (inferred fact).

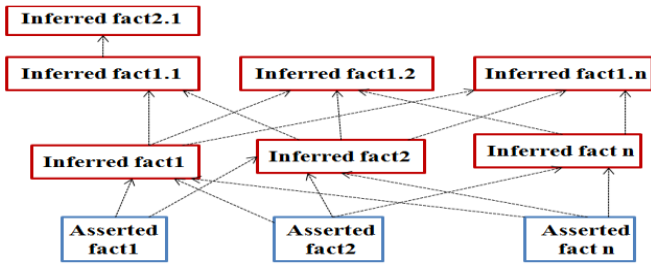


Figure 6. Forward chaining reasoning strategy

The forward chaining algorithm (Algorithm4) is represented below:

```

Algorithm4: Forward chaining strategy
1. Initial facts are submitted by the user to be stored into the database (working memory);
2. Verify the left side of the production rules;
3. If the antecedent part of a rule (IF part) matches, then the rule fires;
4. Execute right side actions;
5. Retract old conditions/facts;
6. Input new conditions/facts;
7. Repeat until no other rules fire;

```

Therefore, in our proposed system, the Jena engine supports the reasoning by retrieving the facts (input) submitted to the decision system and matching them with the rule base to identify rules that satisfy the input. These rules are executed in Jena as see in Figure 7.

```

// read ontology
FileInputStream fileInputStream = new FileInputStream(filePath);
InputStreamReader inputStreamReader = new InputStreamReader(fileInputStream, charsetName);
Model model = ModelFactory.createOntologyModel();
model.read(inputStreamReader, s: null);

// define rule
String rule = "[Rule2: Project_Risk(?PR) ^ HasOccurrence(?PR,?Probability) ^ swrlb:greaterOrEqual(?probability,0.8) ^ swrlb:lessThanOrEqual(?probability,1) ^ HasImpact(?PR,?Impact) ^ HasValue(?Impact,high) ^ HasRating(?PR,?Rate) ^ HasValue(Rate,50) -> HasScore (?PR,?Score) ^ HasValue(Score,100) ^ HasExposure(?PR,exposure) ^ HasValue(?exposure,veryhigh)]"
+ "[Rule3: Project_Risk(?PR) ^ HasExposure(?PR,exposure) ^ HasValue(?exposure, Low) ^ ProjectManager(?x) ^ + Perform(?x,Plan Risk Responses) -> Drop(?x,?PR,Risk mitigation plan) ^ Update (?x,Riskregister)]";

Reasoner reasoner = new GenericRuleReasoner(Rule.parseRules(rule));
InModel inModel = ModelFactory.createInModel(reasoner, model);

```

Figure 7. The reasoning execution in jena

### IV. Specification and implementation case

For implementing such system, there is a need for an approach that defines its reasoning model. Three main approaches are proposed [33] which are (1) case-based system, (2) rule-based system and (3) model-based system where each one has a specific reasoning model. The case-based and rule-based approaches focus on capturing the inferential aspects of knowledge more than expressing the conceptual components and the dependencies among them. The model-based approach is interested in modeling the domain knowledge and realizing the computational system. To develop our DSS, a hybrid approach combining model-based and rule-based approaches is proposed where the knowledge of the domain is modeled and expressed in the form of inference rules. Based on, our reasoning model supports three main components (see Figure 8) respectively the knowledge base, the inference engine and the user interface.

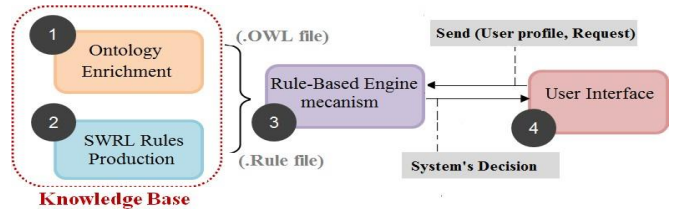


Figure 8. The implementation process workflow

As described in Figure 8, the implementation workflow exploits the OL process to model the PRM Knowledge Base (KB) that contains PR concepts with their relationships, formally represented into the owl file. As well, reasoning rules encoded in SWRL syntax and predefined in the rule base (.rule file). The rule-base engine takes as inputs the rules from rule file, user profile and request from owl file, since this reasoning component has a workspace memory in which a copy of rules and knowledge is captured and imported.

When a team member submits a request through the user interface, this request passes onto the rule engine. Upon receipt of this information, the engine will be associated to the rule file and bound to the owl file to create inference. At step (3), the engine checks whether the antecedent of a rule is filled prior to infer the appropriate rule. The result of the fired rule is then used to trigger other rules. In this way, the system uses the engine to parse the knowledge stored in the owl file against the rules defined in the rule file to produce an accurate decision. The final result returned by the engine and made available to the team through user interface (4).

#### A. System specification

The proposed DSS was designed using UML. We considered the rule\_1 as a sample using flowchart diagram as depicted in Figure9 which describes the workflow that meets the Rule\_1 with all decisions and branching logics.

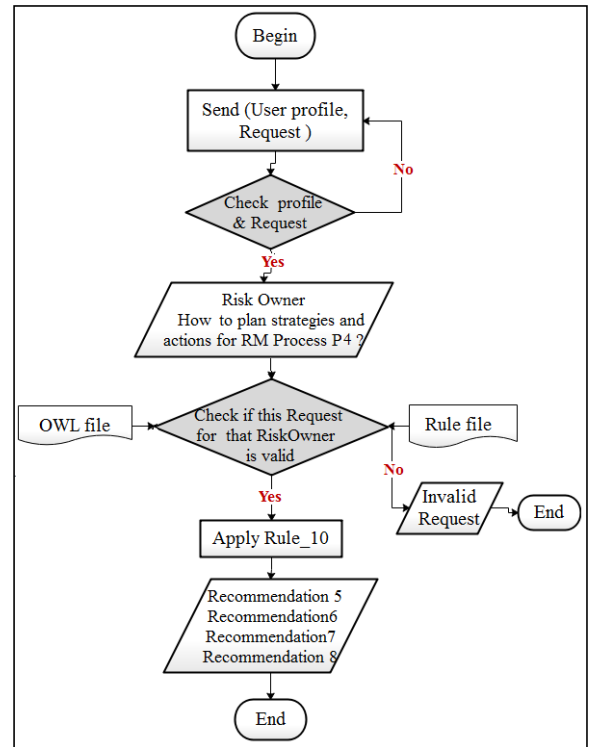


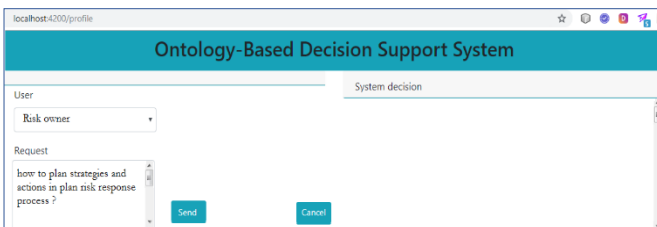
Figure 9. Flowchart diagram based on rule\_1

Then, the algorithm 5 describes the pseudo code of our reasoning model, corresponding to Figure 9:

**Algorithm 5: the reasoning model works**

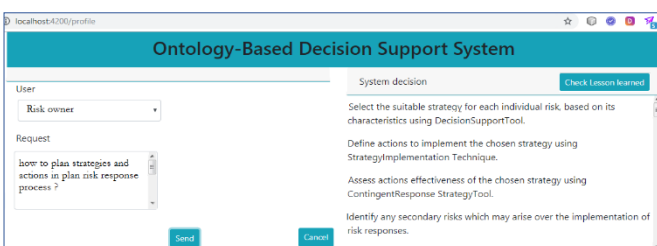
1. Start. The ontology is loaded to access PRM instances using OWL and Jena APIs.
2. The rule base is loaded from URL:  
*List Rules=Rule. Rules from URL*  
("file:myrulefile.txt")
3. Select its profile and submit its request. This information's will be sent and checked by the system.  
*//Two cases may occur*
  - 3.1. **IF** this checked information is valid then  
Step1.1. Create an instance of raisoner with a rule set:  
*Reasoner reasoner = newGenericRuleReasoner (rules)*  
Step1.2. Run the raisoner to match the rule file and bound to the ontology file by creating an inference model (apply the rule\_1).  
*InfModel*  
*inference=ModelFactory.createInfModel(reasoner, data);*  
Step1.3. The result returned by that model will be queried. Thus, if the consequent of rule\_1 is met, the engine infers recommendations (5, 6, 7 and 8) that will be displayed in the user interface.
  - 3.2. **ELSE**, an error message will be displayed.
4. End.

Having the PRM-ontology and the set of rules, the proposed DSS was developed using Java, OWL API and Jena inference API in Net Beans environment, and complemented with an illustrative case (the Rule\_1). Figure 10.a displays the screening of user profile view where the project teams, in particular risk owner, selects its profile and submits its request.



**Figure 10.a.** the screening of user profile views

By clicking on the "Send" button, the system detects the request and the user's profile. Then, it matches user profile with his request against the information stored in the rule.file. If the match is found, the system deduces the associated knowledge using IsRecommendedTo object property. Thus, decision will be presented as list of recommendations that are inferred and reasoned from SWRL rules and displayed in natural language as shown in Figure 10.b.



**Figure 10.b.** DSS result from raisoner and rule matching

**V. Potential benefits from a questionnaire survey**

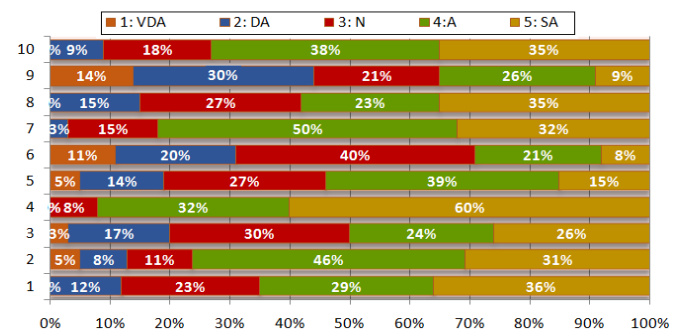
To acquire opinions and in-depth insights of practitioners and professionals and then assess the potential benefits of our DSS, a questionnaire survey was undertaken, where the main investigation items (10 items) with their results are summarized in Figure 11.

During survey, we introduced the main functions and features of the proposed DSS, where the respondents are asked to verify the system functionality and then fill the questionnaire giving their feedbacks (suggestions, issues or questions). The presented questionnaire is available in this link <https://fr.surveymonkey.com/r/77WPZQS>.

For each item, respondents are requested to rank their agreement level based on a five-point Likert scale [1= very disagree (VDA), 2= Disagree (DA), 3= Neutral (N), 4= Agree (A), and 5= Strongly Agree (SA)]. Items ranked as "Disagree" or "Very Disagree" requires further explanations.

From this study, email addresses to a total of 147 potential experts, represents the top PRM influencers on Project Management.com forum, including project manager, PMP consultant, risk engineer, research associate, risk doctor and risk owner, are selected and qualified according to their own knowledge and experience [8year-32year].

Through survey monkey mailing system, a total of 66 valid responses have been received, yielding a response rate of 45%.



**Figure 11.** Results of research survey

From Figure 11, despite the small sample size, the overall feedback is on positive side which amounts that for each item, except "item 6 and 9", the total proportion of the rank "Very Agree" and "Agree" is greater than "50%", that's still prove the applicability and benefits of the DSS.

From this analysis, the following discussions are made. (i) It's found that all of survey respondents substantiate the interests of a commonly vocabulary of risk-related concepts in agreement with standards (92% ~ 61 respondents). This viewpoint coincides with El Yamami et al. [10] study in which authors underlines the necessity of conceptual metamodel for IT PRM based on PMI's standard. (ii) Even almost of them (54 respondents) are aware about the need of an integrated decision support tool for PRM covering the five processes with their T&T. In the same line, they believe that the prototype system can inform them what PR may occur, which are its causes and how to develop its response strategies (58%). (iii) Nonetheless, most of them are very concerned about a key issue which is the lesson learning process (40%), since they accustomed that lessons learned are included in organizational process assets reports. This issue could be solved by adding



semantic indexing module that enriched the document database integrated in the system. Meanwhile, 21% of respondent' responses suggest a history database should be integrated in order to store the explicit knowledge (documents, reports) for forthcoming projects. (iv) Also, we noticed that 44% of respondents perceived the experience of using a software tool as only marginally acceptable. In practice, domain experts are not familiar with semantic tools and rule base development, so it may be difficult for practitioners to change their working practices.

Then, we discuss our significant findings by measuring the perceptions of domain experts related to item importance, as illustrated in Fig. 12, using Mean Score (MS) ranking analysis, computed by the following formula [34]:

$$MS = \frac{\sum(f*s)}{N} \quad (5 \geq MS \geq 1) \quad (6)$$

Where:

MS: mean score of items; S: score given for each item [1, 5]; f: frequency of response to each rating, for that item; and N: number of respondents concerning that item.

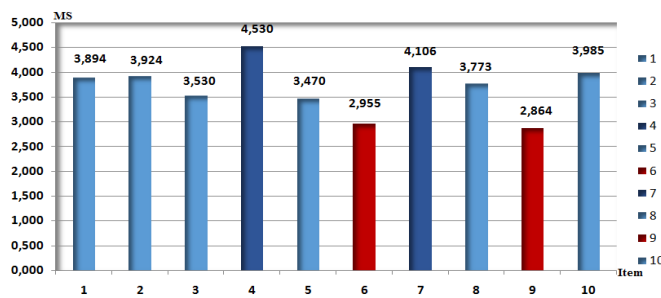


Figure 12. The mean score results

The mean scores ranged from 2.8 to 4.5, suggesting that the item ranges from moderate to high levels as presented in the bar chart (Figure 12). For items 4 and 7 have the highest score 4.5 and 4.1, respectively. The rest are rated between 3.46→3.9, except for item 6 and 9. It can be interpreted that these latter are less important (the mean score is respectively 2.9 and 2.86).

## Conclusion

In order to assist practitioners and researchers to better study the potential impacts of their decisions and assess the PR as precisely as possible, we have developed an Ontology-based Decision Support System, relying on PMI's framework for knowledge retrieval and adopting a hybrid approach for knowledge modeling and reasoning. Our approach is based on the OL from unstructured corpus (PMI's standard for PRM) to enrich an existing domain ontology called PRM-Ontology. To this end, the OL process starts with analyzing the PMI's standard by the NLP pre-processing techniques. Then, the relevant terminology extraction is conducted to identify synonym of terms, concepts formation, concept hierarchy organization, learning relations, relations discovery as well as rules and axioms extraction. Once the OL tasks, we updated the PRM-ontology by adding the candidate elements. The ontology enrichment process treats concepts, OWL axioms and integrates SWRL rules to enhance the knowledge recommendation process. The enriched ontology achieved

0.82 precision, 0.67 recall and F-measure value of 0.74. We also implemented a rule-based reasoning mechanism for inferring recommendations using Jena\_engine. The proposed framework is supported by a software tool with an illustrative validation scenario to demonstrate how the system operates for a specific case during the PRM processes. Further, the benefits and limitations are investigated through the questionnaire where the survey finding proves that our decision system can improve effectively the PRM decision making from the perspective of practitioners and researchers.

Although the study objectives were achieved, future efforts can be made to develop a semantic indexing module, based on the semantic annotation approach using NLP techniques and the Gate framework, to provide a set of reference documents or reports related to a specific case, which make the team tasks easier in making decision supported by some references. Once the documents have been annotated, the semantic indexing module assigns a weight to the annotations to reflect how relevant the ontology concept is for the document meaning. Further, in-depth case studies would be launched to compare the potential benefits of this approach with and without ontological reasoning.

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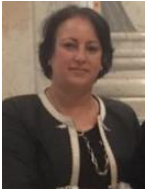
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