Manuscript File Click here to view linked References

Context-Driven Ontology-Based Risk Identification for Onshore Wind Farm Projects: A Domain-Specific Approach

Emad Mohamed[a], Nima Gerami Seresht[b], and Simaan AbouRizk[c]*

[a]5-080 NREF, University of Alberta, 9105 116 St., Edmonton, Alberta T6G 2W2, Canada; ehmohame@ualberta.ca

[b]Department of Mechanical and Construction Engineering, Northumbria University, Newcastle upon Tyne, United Kingdom, NE1 8ST; nima.gerami@northumbria.ac.uk

[c]5-080 NREF, University of Alberta, 9105 116 St., Edmonton, Alberta T6G 2W2, Canada; abourizk@ualberta.ca*Corresponding author:

Simaan AbouRizk
Professor
5-080 NREF
University of Alberta
Edmonton, Alberta
Canada T6G 2W2

ABSTRACT

Risk identification is a knowledge-based process that requires the time-consuming and laborious identification of project-specific risk factors. Current practices for risk identification in construction rely heavily on an expert's subjective knowledge of the current project and of similar historical projects to determine if a risk may affect the project under study. When quantitative risk-related data are available, they are often stored across multiple sources and in different types of documents complicating data sharing and reuse. The present study introduces an ontology-based approach for construction risk identification that maps and automates the representation of project context and risk information, thereby enhancing the storage, sharing, and reuse of knowledge for the purpose of risk identification. The study also presents a novel wind farm construction project risk ontology that has been validated by a group of industry experts. The resulting ontology-based risk identification approach is able to accommodate project context in the risk identification process and, through implementation of the proposed approach, has identified risk factors that affect the construction of onshore wind farm projects.

Keywords: *risk management; risk identification; onshore wind farm; ontology; knowledge management; construction*

1. Introduction

By 2050, approximately 35% of worldwide electricity demands are anticipated to be supplied by onshore and offshore wind farms [1]. Expanding the capacity of wind energy to meet this demand will require the large-scale construction of turbines and grid systems. An important step in the pre-construction stage of wind farm projects is risk management. The construction phase of wind projects may be hindered by various types of risks [2], which must be appropriately managed to ensure project objectives are completed on time, within budget, and in adherence to environmental and safety regulations [2,3]. Onshore wind projects are a unique type of construction project that are characterized by repetitive construction, where each project has several turbines that are constructed in a similar way. As a unique type of construction process, onshore wind farm construction is characterized by unique risks. Also, onshore wind projects are relatively new types of construction, thus available data and reference materials are either scarce or of low quality [2]. As such, existing risk registers for onshore wind farm construction are broad, encompassing risks that may not be applicable to all projects while omitting contextual or project-specific risks. Thus, risk management in wind farm projects remains a relatively unexplored field of study, resulting in a lack of applicable risk management decision-support systems suitable for onshore wind farm construction. Current risk identification methods in wind farm construction, therefore, lack the capacity to map specific project characteristics to identified risk factors. This limitation prevents the contextualization of historical data, requiring risk analysts to manually evaluate the similarity between previous and current projects. This is a time-intensive process that involves the review of data across multiple, fragmented databases and the tedious mapping of risk factors to the specific characteristics of a new project [2].

The first step of the risk management process is risk identification. Here, various aspects of a project, including financial, environmental, social, regulatory, and/or political considerations [4], are reviewed to identify factors that may result in schedule delays, cost overruns, or other safety or environmental concerns. In current practice, risk analysts obtain specific details (i.e., context) of a project from incompatible and fragmented data sources (e.g., expert experience, historical project information, construction plans, and other project-related documentation) before comparing the project under study to similar historical projects and curated risk registers to identify potential risks for a new project.

Several risk identification techniques were proposed in the literature, which can be categorized as traditional [5] or advanced [6]. Traditional risk identification techniques such as risk registers, Delphi method, and interviews are limited by several barriers, including (1) the requirements of experts to review a significant volume of project documents, (2) the inability to automatically discover and map relationships between risk knowledge that exists in the same or in different documents, and (3) the dependency of output quality on the recall accuracy of experts. Advanced risk identification techniques have also been proposed in the literature, such as case-based reasoning [2] and rule-based systems [4]. However, existing techniques (e.g., case-based reasoning [2]) can typically only consider higher-level project information and are limited by their inability to consider specific project details and contexts [2]. If capable of considering project specifics (e.g., rule-based models [4]), they are limited by the need to create long lists of mapping if-then rules for each new project. These if-then rules are used to associate the contexts of the project that require risk identification with the contextual information of previous projects so that risks can be identified as potential risk factors. Although models (e.g., case-based reasoning [2] and rule-based [4]) for automating the mapping of risk factors with project characteristics have been developed, they focus on mapping risks at a high level and cannot consider the specific, contextual characteristics of individual projects. This is particularly important in wind farm construction, as the specific regulatory, environmental, social, and geographical context of a project can substantially impact the types and severity of risks on project outcomes. For example, a risk factor of damage to existing infrastructure that was identified in a previous risk register of an onshore wind project may not apply to another onshore wind project until the context of that project is defined and information about existing infrastructure is determined.

Recently, risk ontologies were shown to rapidly map safety risks [7–9] to specific projects in construction. While promising, these studies [7–9] were limited to specific risk factors (e.g., safety risks) and cannot, therefore, be used to compile a comprehensive list of all risk factors (e.g., financial, environmental, etc.) present during the construction phase of wind farm projects. Building upon the current-state-of-the-art, the present study has developed a unified, ontology-based model to automate the context-driven identification of risk factors in onshore wind farm construction. A domain-specific risk ontology model, which functions as a knowledge base for the storage, reuse, sharing, and recall of risk information, was built from historical project data and was validated by a group of subject matter experts. Once validated and verified, the model was used to develop a context-driven risk identification ontology.

In recent years, there has been a large development of advanced quantitative risk management techniques due to their enhanced accuracy and usability over traditional techniques [10]. Despite these improvements, advanced techniques are rarely applied in construction practice [11]. Abdulmaten Taroun [10] conducted a comprehensive literature review of risk management techniques used in construction since 1980. In this study, Taroun concluded that, while numerous theories and techniques for improving risk management in construction have been proposed, these theoretical advancements are not being translated into advances in construction practice. These findings align with those of a recent study by Jung and Han [12], which reported that, because of a lack of knowledge and real-world applicability, practitioners continue to rely on experienced-based, traditional risk management approaches. Advanced risk management techniques described in the literature are often presented using simple illustrative examples or generic project information [13]. Although this approach of presenting advanced risk management techniques was useful for demonstrating method generalizability, construction practitioners often have difficulty adapting and applying these generic methods to a specific project [13]. Domain-specific models allow for a better understanding of the model by industry practitioners and also facilitate model development and experimentation. This study presents the first reported application of an ontology-based approach to develop a domain-specific risk identification model that can easily be emulated and implemented by industry practitioners in any onshore wind project. The domain-specific model is used to identify the context-driven risk factors of wind farm projects.

This study contributes to the body of knowledge by (1) proposing a domain-specific context-driven approach for risk identification in onshore wind projects. Domain-specific techniques such as this are expected to facilitate the adoption and application of ontologies by industry practitioners to more effectively identify construction risks in onshore wind projects., (2) extending the application of ontology to the identification of risk factors associated with the construction of onshore wind projects, and (3) reducing the time and effort required to map risks to specific project contexts by automating the risk identification process, thereby improving the storage, reuse, and recall of risk-related knowledge.

2. Literature review

2.1 *Risk identification in onshore wind farm projects*

A risk factor is defined by the Project Management Institute (PMI) [14] as "an uncertain event or condition that, if it occurs, has a positive or negative effect on a project's objectives". Risk identification is the process of systematically and continuously identifying, categorizing, and assessing the initial significance of the risk factors associated with a construction project [15]. Risk identification is considered the most important step in the risk management process [16,17], as unidentified risk factors cannot be controlled or mitigated [18,19] and, therefore, impose unassessed threats to project objectives [18].

Numerous research studies have focused on identifying the risk factors affecting the entire lifecycle of a wind farm project, including design, construction, operation, maintenance, and/or decommissioning. Many of these studies have relied on published literature and/or questionnaire surveys. For example, Gatzert and Kosub [3] presented the risk factors affecting onshore and offshore wind farm projects in Europe, including risk factors at different phases of the project lifecycle and risk mitigation strategies for the proposed risks. In a similar study, Angelopoulos and colleagues [20] investigated the risk factors affecting the planning, construction, and operation of onshore wind energy projects in Europe. Another study identified and presented the risks and challenges that face the design, planning, construction, and control of small wind turbine projects in Italy with respect to time, cost, and quality [21]. Other studies have reviewed the risk factors affecting the entire lifecycle of onshore wind farm projects [22], risk factors in implementing wind energy projects along with proposed mitigation strategies for those risks [23], and risks facing solar and wind energy projects along with the available risk mitigation strategies that can contribute to the sector's growth and long-term sustainability [24].

Much of the risk identification literature in onshore wind farm construction has focused on the identification of the risks themselves as opposed to the development of advanced methods for identifying risks. As such, these studies have not addressed the challenges associated with the management and representation of knowledge for risk identification. The importance of project context and knowledge representation in risk identification is detailed in the following section.

2.2 *Project context and knowledge representation*

Context is defined by Dey [25] as "any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". With respect to the risk identification problem, entities are risk factors and the information used to identify the risk factors is the project context. From a construction perspective, Boukamp and Ergen [26] defined context as specific project conditions on site (such as the project components that are built), activities performed, and resources used. Dey [25] further outlined three important features of context-aware modeling techniques, specifically that (1) the system has the ability to present information and services to the user; (2) the system can automatically execute services for a user; and (3) the system can link context and information together to enable reasoning and retrieval.

Consideration of project context can be achieved through knowledge representation, which is the process of recording and coding real-word domain knowledge using communicative media to allow reasoning [27,28]. The five main categories of representation techniques include object-, network-, frame-, logic-, and semantic web-oriented [29] representation. Object-oriented representation allows information to be organized as objects that communicate with each other [29]. Each object is defined by private properties (i.e., attributes) and methods (i.e., procedures)

[29]. Objects can only communicate with each other through messages [29]. Network-oriented representation allows knowledge to be represented visually through a network of interconnected nodes, each representing different entities that have various relationships [29]. Frame-oriented representation, which is often used in natural language processing, allows all information relevant to an entity to be arranged together in one structure associated with that entity [29]. Logic-oriented representation makes use of rules that deal with propositions, where a conclusion can be drawn based on different conditions. Lastly, semantic web was developed to represent generic knowledge, such as concepts, their relationships, and how they are semantically associated [27].

Risk management is often complicated in construction by the fragmented nature of construction data, where various data are stored in isolated data islands. As such, risk management in construction requires a systematic model for risk management that allows the consideration of complex risk sources and their causation mechanisms [30]. A change in project context can significantly influence the risk factors of a project [31]. Incorporating project context with risk factors allows risk analysts to identify context-oriented risk factors instead of relying on a generic list that may not apply to the current situation [4,32]. Considering context descriptors is beneficial for accurate recognition and for determining potential relationships between risk factors and their sources [30]. Ignoring project context information increases the burden on analysts due to the effort required to select the risk factors that are most relevant to the current project [4,32]. Furthermore, the use of knowledge acquired from previously-executed projects is often limited without an explanation by the practitioners involved in these projects regarding the context and relationships between data [33].

Recent work by Kifokeris and Xenidis [34] suggested that risk factors and sources should be contextually and methodologically integrated with other technical project information. Context modeling approaches were classified by Wang and colleagues [35] into formal and informal modeling. Formal context modeling adopts formal approaches for manipulating contexts to enable reasoning about contextual knowledge. Conversely, informal context modeling is often based on proprietary representation schemes that do not permit reasoning about contexts in a single system [36], nor share any understanding about context easily between different systems [35]. Although a majority of context models employ classification systems to structure contextual information, only a few allow association relationships between contextual information without considering the semantic relationships [36]. Existing methods for identifying risks in construction are detailed as follows.

2.3 *Risk identification techniques in construction*

Risk identification techniques can be classified as either traditional methods or advanced methods. Generally, traditional techniques implement the risk identification process manually without any support from information and communications technology (ICT) techniques [5], while advanced techniques tend to automate the risk identification process using some form of ICT techniques [6]. Brief descriptions of both traditional and advanced techniques, as well as promising developments in each category, are provided.

2.3.1 Traditional techniques

Manual documentation review, where risk factors are identified through a review of documents from the current project or similar projects, is one of the most common traditional risk identification approaches [17,19]. Time-consuming and laborious, documentation review relies heavily on the quality of both the documentation and expert judgment for identifying risk factors, as well as on the ability of experts to discover relationships between knowledge that exists in the same or different documents.

Other common traditional techniques rely solely on expert judgment for risk identification [19]. In the Delphi technique, a group of experts are asked individually about the relevance of each potential risk factor to the project; then, their opinions are aggregated and recirculated among the participants until a consensus is reached [37,38]. The brainstorming technique can also be applied. This technique begins with the presentation of the overall objectives, followed by a free and open dialogue to encourage the identification of risk factors [38–40]. Another common technique is one-to-one interviews. Here, interactive dialogue is used to elicit risk factors directly from interviewees [18], where experts are interviewed directly about the risk factors in a project. Although the Delphi technique, brainstorming, and interviews do not rely on project documents for risk identification, these techniques depend on expert recollection of previous experiences and their comparison to the project under study. A dependence on expert recall can result in certain risk factors being unintentionally omitted. Notably, Goh et al. [40] have recommended the implementation of a database interface between project team members to streamline communications during brainstorming sessions.

Using checklists developed from previous projects [41], or lessons learned [37] as a memory aid, is another traditional technique for risk identification. Often used as a starting point in the risk identification process [17], checklists alone cannot link risk factors to specific project contexts. Risk registers, which use recorded data from previous projects including information about the risk factors, response strategies, required resources, risk impact, and risk allocation [4,42] to identify risk factors for a new project [19], may also be used for risk identification. Although risk registers provide more information compared to other traditional techniques, risk registers, much like checklists, lack the capacity to automatically map risk data to each other. Lastly, diagramming or graphical techniques, including cause-and-effect diagrams, system or process flow charts, and influence diagrams, have been used to identify risks in construction projects [17,19]. These techniques are used relatively infrequently in construction [19,38], and similarly to other traditional risk identification techniques, the accuracy of diagramming techniques relies on the recall accuracy of experts.

Traditional risk identification techniques are limited by several barriers, including (1) the requirements of experts to review a significant volume of project documents, (2) the inability to automatically discover and map relationships between risk knowledge that exists in the same or in different documents, and (3) the dependency of output quality on the recall accuracy of experts.

2.3.2 Advanced techniques

A number of studies have attempted to address the limitations of traditional risk identification techniques through the development of advanced risk identification methods. Some researchers have suggested the use of case-based reasoning for risk identification. For example, Somi et al. [2,43] proposed a fuzzy case-based reasoning model to support risk identification in onshore wind projects. However, the first study [2] focused only on a specific component of the project (i.e., tower assembly). Moreover, both studies [2,43] lack the ability to represent risk knowledge and project context information. Lastly, after retrieving a list of risk factors of a similar project, the risk analyst must decide which risks apply to the new project using their expert judgment, which takes additional time and effort. Zou et al. [44] proposed case-based reasoning and natural language processing to retrieve similar cases from previous projects. Although able to more rapidly identify project risks, these methods are unable to consider the detailed context of a project during the identification process in addition to the need for manually determiningwhich risk factors are relevant to the project being analyzed.

De Zoysa and Russel [4,32,45] suggested the use of project context to identify the risk factors of a construction project using a rule-based system. Their risk identification framework consists of three primary components: a standard library (standard templates), current project context, and rule sets. The standard library allows the user to define the project context for sources of risk factors, including financial, social, environmental, political, and regulatory aspects. The current project context component allows the user to define the attributes and parameters of the current project. The rule sets allow communication between the current project context and the standard library. Although able to consider the specific context of a particular project, the rule sets that link the current project to the standard library must be defined manually for each new project. Requiring considerable time and effort, existing rule-based systems do not represent a considerable improvement in terms of laboriousness and time. Recently, evidence demonstrating the potential of ontology-based approaches to address these gaps has been reported, with several studies demonstrating promising results in other application areas. For example, Xing et al. [7] developed an ontology model to identify risks in a metro construction project, Aziz et al. [46] proposed an ontology model to represent the knowledge of safety hazards during petrochemical operations, and Cao et al. [30] presented an ontology model to support the identification of accidents during railway operations. Osorio-Gómez et al. [47] proposed an ontology approach for risk identification of operational risk management in a supply chain with third-party logistics providers. Although promising, these studies were limited to a specific set of risk factors in other application areas. The ability of these existing approaches to identify and assess a comprehensive set of all risk factors present during construction, therefore, remains limited. Although rule-based systems and ontology-based approaches are both considered knowledge-based systems, ontology-based approaches allow direct mapping and linking of contextual information with risk information. This feature of ontology-based approaches eliminates the need to develop a lengthy (and time-consuming) list of if-then mapping rules required for the development of a rule-based system. Although still in its infancy, the development of an ontology-based risk identification approaches has been described in a few studies. A description of ontological modeling in construction and for risk identification is detailed as follows.

2.4 Ontologies in construction and risk management

A fundamental key to proper and successful risk management is the ability to share information between different technical and management teams in a project [46]—a process requiring a unified language, terminology, and information [46]. Ontology, as a means for information storage and transfer, is a widely used approach for knowledge representation and modeling, especially when knowledge is highly interconnected and linked [48]. Key objectives that can be achieved by the development of ontologies have been described by Noy and McGuinness [49]. These include (1) to share a common understanding of the structure of information between people or software agents, (2) to enable the reuse of domain knowledge, and (3) to analyze domain knowledge.

Ontology represents domain knowledge as a set of concepts along with the connections (i.e., relationships) between them [50–52]. Compared to a traditional database schema [7], ontologies enable the presentation of knowledge with explicit and rich semantics [52].. Ontology development typically begins with schema of the domain model, which describes the main components of knowledge to be considered [53]. Then, a taxonomy is used to organize subconcepts contained within each of the main components [54]. A taxonomy allows for the organization of concepts into concept schemes through a hierarchy of classes and sub-classes [54]. A class is a collection of instances that can encompass sub-classes within its taxonomy. Relationships are used to describe the connections amongst the classes and sub-classes of the ontology. The various features and attributes of the classes and sub-classes are defined by properties. Instances are the basic components of an ontology, which fill the defined properties of the classes and sub-classes [49]. Ontology-based approaches have two advantages, specifically (1) they are able to model context variables and semantic relationships in one unified framework, and (2) they can be used for reasoning purposes to infer the characteristics of a system with new conditions.

Ontologies have been widely applied in construction management to model the domain knowledge of construction concepts. Leading research in this area was originated by El-Diraby et al. [51], who proposed a domain taxonomy of construction knowledge that provided a foundation for the development of domain ontologies of urban civil infrastructure [55], highway infrastructure [56], and generic construction domain knowledge [50]. Existing ontology-based approaches to model risk knowledge in construction remain limited. One subset of ontology-based studies has limited their scope to a specific set of risks; therefore, a comprehensive set of strategic project level risks cannot be identified using these methods proposed by the authors of the aforementioned studies. Examples include the use of ontologies to identify safety hazards related to specific construction methods, such as metro construction [7,8]; to model the safety requirements and standards for active fall safety hazards [9]; or to identify safety hazards in construction projects [57–59]. These ontologies were able to achieve the purpose they were created for, which is modeling knowledge of safety hazards related to a specific construction method at the activity level. Although an ontology-based approach was used in the aforementioned studies, risk knowledge at the strategic project level was not modeled, and the studies overlooked other risk factors related to cost, time, quality, and the environment.

A second subset of studies have focused on improving knowledge management and transfer between different phases of the risk management process at the project level. For example, Tserng and colleagues [60] proposed an ontology-based risk management model for representing risk factors' knowledge to enhance information flow in both the identification and assessment phase of the risk management process. Importantly, however, their model did not consider the specific context of a project, limiting the ability of their model to support context-driven risk identification in practice. Meditskos and colleagues [61] and Angelides and colleagues [62] proposed an ontology model to facilitate the integration of risk assessment practices from various domains and to provide unified terminologies for managing risks in industrial projects. Similar to the study of Tserng and colleagues [60], the coverage and comprehensiveness of Meditskos and colleagues' [61] model were limited (i.e., only a high-level ontology model with few details regarding the taxonomies in each sub-ontology was presented). Therefore, existing models are limited due to their inability to consider the semantics of the contextual information required for proper identification of risk factors. Nevertheless, these previous models laid the foundation for the current study by suggesting that ontology-based modeling may represent a potential approach capable of addressing the challenges related to context and semantic modeling in risk identification [36].

Although no single ontology can fully cover all domains, nor can a single ontology satisfy the needs and preferences of all users [56,63], domain-specific ontologies for application to a certain project type can be designed. An ontology for improving knowledge management during risk identification in onshore wind projects, however, has yet to be developed.

2.5 *Research gaps*

Several limitations of advanced risk identification techniques that must be addressed to progress the state-of-the-art have been recognized in the literature:

1. While existing rule-based models [4,32,45] are capable of integrating risk factors with specific project contexts, the modeling approaches proposed require practitioners to exert a considerable amount of time and effort to develop the rules that map risk factors to their context.
2. Although less laborious, existing case-based reasoning models [2,43,44] lack the capacity to consider detailed project contexts and, when mapping to corresponding risk factors, prevent automated reasoning and identification of related risk factors.
3. Existing ontology models developed to support risk identification in construction focus on only:
    a. a specific set of risk factors [7,30,46,47,60–62], or
    b. risks at the activity level [57,58].
4. Ontologies designed to support risk identification in onshore wind projects have not yet been developed.

3. Proposed framework

To address the aforementioned gaps, the present study has developed a domain-specific risk ontology for onshore wind farm projects that is capable of identifying a context-driven list of project risks relevant to the execution phase of construction projects. The risk ontology was then incorporated into a framework designed to enable the rapid, automatic identification of various risks in consideration of detailed project contexts. The proposed framework consists of three steps as shown in Fig. 1: (1) ontology population, (2) current project data collection and input, and (3) risk factor identification. The methodology used to develop the ontology, as well as a description of the proposed framework, are detailed in Sections 3.1 and 3.2, respectively.

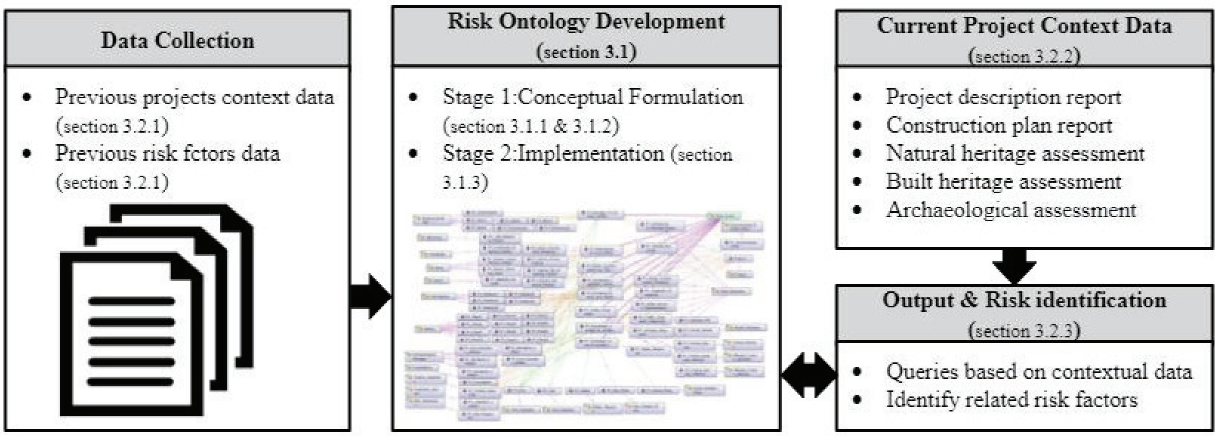

Fig. 1. Proposed ontology-based framework for risk identification.

3.1 Ontology development

First, the domain-specific risk ontology that is incorporated into the framework was developed using the method proposed by Noy and McGuinness [49]. The methodology consisted of a conceptual formulation stage and an implementation stage. The conceptual formulation stage (Stage 1) included six steps (Fig. 2). The first was a knowledge extraction step, where the domain and scope of the ontology was determined. This was followed by ontological preparation steps, where important terms were enumerated, and the following terms were defined: classes and class hierarchy, relationships between classes, properties of classes, and instances within classes. Conversely, the implementation stage (Stage 2) consisted of two steps, specifically ontology implementation and evaluation. An overview of the methodology used to develop the ontology is presented in Fig. 2.

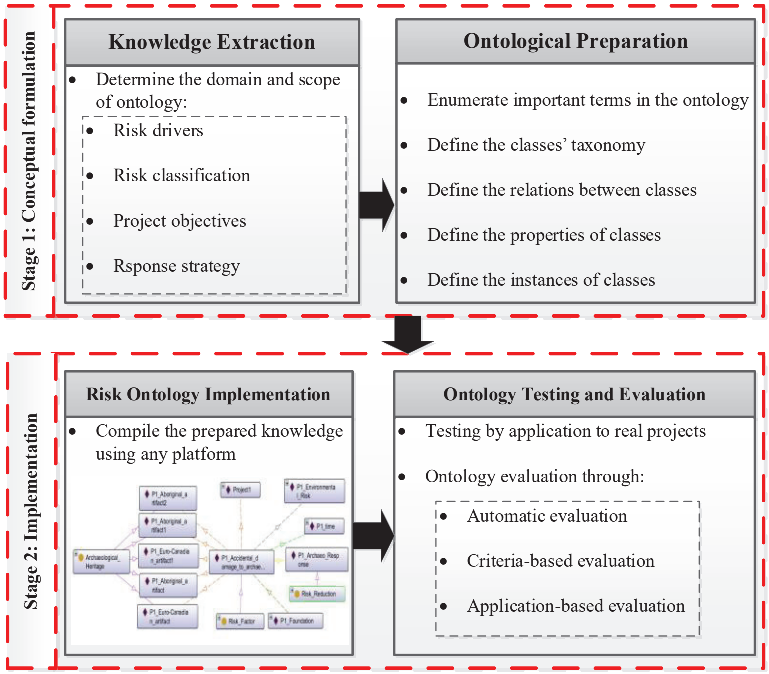

Fig. 2. Ontology development methodology.

3.1.1 Knowledge extraction

In the knowledge extraction step, competency questions that focus on determining the purpose, scope, level of formality, intended uses, and end-users of the risk ontology were established based on those recommended in literature [55,56]. Questions in the present study included "What is (are) the purpose(s) of the ontology?", "What parts of the risk management process should be covered by the ontology?", "What information should be captured in the ontology?", and "Who are the end-users of the ontology?". Competency questions formulated as queries are presented in Table A.1.

It was determined by the present authors that the ontology should focus on the identification stage of the risk management process to support the project planners, project managers, and decision makers involved in the risk identification of onshore wind projects. As such, information related to the drivers or sources of the risk factor, the response strategy developed to mitigate the impacts of risk factors if they occurred, and their effect on the project and objectives of the project were included as classes of this particular ontology.

Once the scope was defined, a schema of the domain model of the ontology was developed to support knowledge extraction and modeling. The schema of the domain model was developed using competency questions and by reviewing previous research related to knowledge-based risk identification [4,31,47,61]. Common classes found across multiple studies, or classes used in previous studies that were well-suited to onshore wind farm construction were identified, as summarized in Table 1. Based on these findings from competency questions and previous research, seven key classes, including (1) risk factors, (2) project, (3) risk drivers, (4) risk classification, (5) project objectives, (6) project work packages, and (7) response strategy, were used to establish the schema of the domain model illustrated in Fig. 3.

Table 1. Summary of classes in previous studies.

Reference	Primary Classes Used
[4]	Risk factors, risk factor classification, response strategies, and physical components
[31]	Risk factors, risk factor classification, work breakdown structure of affected project components
[61]	Case study, risk case, risk, risk variable, category, and impact category
[47]	Risks, sources of risk, frequency, impact, managerial strategies, and logistics companies

It is also common practice for domain experts (groups of 3–10 experts) to be involved in the iterative development and evaluation of ontologies (in contrast to using a mass survey approach) [56]. Here, a focus group consisting of six experts in risk management, as detailed in Table 2, evaluated the schema of the domain model and confirmed that the content analysis was complete and that ontology development could begin.

Table 2. Demographic information of focus group experts.

No.	Position	Industrial Experience (years)	Education
1	Vice President	20	M.Sc.
2	Project Manager	18	B.Sc.
3	Project Manager	15	B.Sc.
4	Risk Analyst	12	B.Sc.
5	Wind Turbine Engineer	10	Ph.D.
6	Project Coordinator	7	B.Sc.

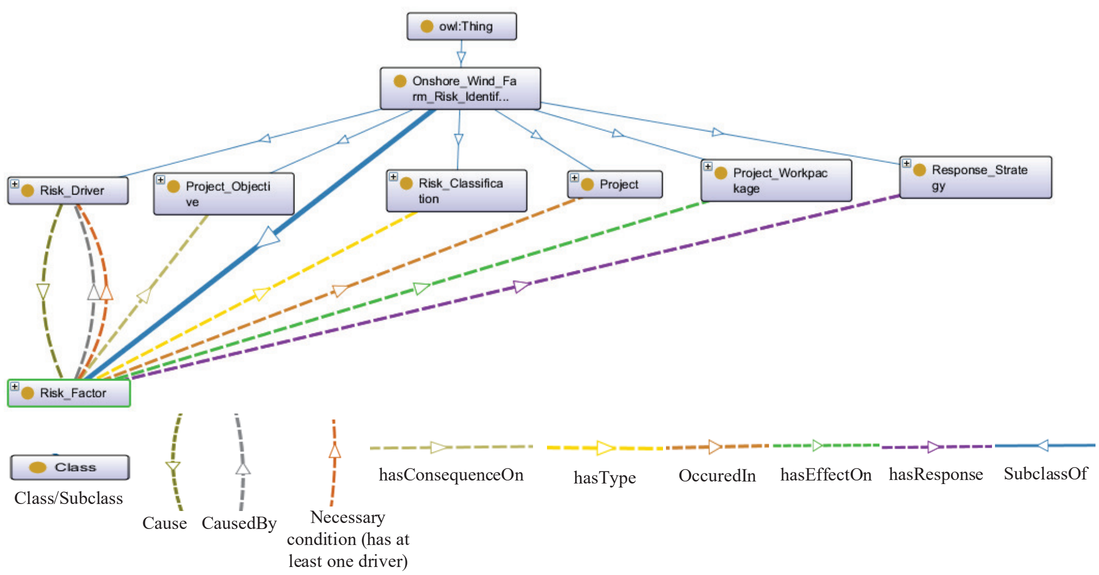

Fig. 3. Schema of the domain model of onshore wind farm risk knowledge in Protégé®.

3.1.2 Ontological preparation

After establishing the schema of the domain model and the main classes that should be modeled in the risk ontology, detailed descriptions of the classes, relationships, and properties were developed. Content analysis was applied to discover the existence of classes within texts, to understand their meanings, and to analyze the relationships between the classes [54]. Following a content analysis of related project records, historical data, and project documents, the classes taxonomy was identified. Consultations with domain experts were used to periodically evaluate the representativeness of the developing taxonomies. In the following sub-sections, each taxonomy is defined. Then, semantic relationships between the classes of the schema of the domain model are detailed. Finally, data properties of the classes and sub-classes are described.

3.1.2.1 Development of class taxonomy

The taxonomy development process typically includes varying degrees of judgments regarding classification and the balance between depth and coverage [51]. A review of existing literature provided the foundation for taxonomy development. Moreover, ontology development best practices proposed by El-Diraby et al. [51], specifically (1) iterative development and (2) involvement of domain experts, were used to support this process. After the first set of expert interviews (i.e., held after the development of the schema of the domain model), a set of preliminary taxonomies, based on available literature, was developed. Then, a second set of interviews with the domain experts listed in Table 2 were held. Subject experts reviewed and evaluated the proposed taxonomy, ultimately resulting in the final taxonomies illustrated in Fig.

It is important to note that similarities of classes between different types of construction projects are expected when developing risk ontology for strategic project-level risk identification. However, it is also expected that certain classes will differ from one project to another. Onshore wind projects are a unique type of construction project that are characterized by repetitive construction, where each project has several turbines that are constructed in a similar way. A typical onshore wind farm project was found to be comprised of eight major work packages: site preparation, pre-construction work, foundation, turbine delivery, turbine assembly, collection system, commissioning, and site rehabilitation [64–67]. This uniqueness of onshore wind projects was considered while developing the risk ontology: sub-classes of two classes were specifically designed for this type of project, namely the “Processes” class and the “Project work package” class as shown in Fig. 4. The sub-classes of these two classes will differ from one project type to another depending on the project work breakdown structure. The reader should consider this distinction when developing risk ontologies for different project types. The development process of each class is detailed as follows.

3.1.2.1.1 Risk drivers taxonomy

Understanding the relationships between the risk factors and their drivers is crucial for effective risk identification. The taxonomy of the risk drivers class was developed based on previous research [4,7,31,32], which proposes that risk identification can be classified into external and internal project contexts. This sub-classification was applied to the risk drivers class of the current ontology, as illustrated in Fig. 4.

Here, the external project context class represents the characteristics surrounding a project, including physical, economic, social, political, and regulatory contexts [4,45]. The first external project context sub-class is the physical class, which represents both the natural and artificial objects surrounding a project. The physical sub-class is further divided into the natural objects sub-class, which includes living organisms and inorganic objects such as geological features and natural resources [4,45], as well as the artificial objects sub-class, which represents man-made objects including existing structures such as buildings, utilities, and other infrastructure. The second external project context sub-class is the economic sub-class, which refers to financial conditions such as inflation, exchange rate, and labor market. The third sub-class is the political context sub-class, which represents federal, state (or provincial), and municipal government characteristics. The fourth sub-class, the regulatory class, refers to the various regulations imposed by the federal, state (or provincial), and municipal governments on project execution, such as environment protection laws, labor and safety regulations, and other municipal by-laws. The final sub-class, the social class, refers to the demographic profile of the project in terms of cultural characteristics of local and First Nations communities.

The internal project context class contains two sub-classes, the process sub-class and the organizational structure sub-class, as detailed in Fig. 4. The process sub-class refers to the various work packages executed during the construction phase of the project that are represented in a typical work breakdown structure. A typical onshore wind farm project was found to be comprised of eight major work packages: site preparation, pre-construction work, foundation, turbine delivery, turbine assembly, collection system, commissioning, and site rehabilitation [64–67]. The sub-classes of “Process” class is specific to the project under study; thus, it will differ from one project type to another. For example, while Bonduel [68] developed a construction task ontology, it cannot be used here as it was developed for heritage buildings. The organizational structure sub-class represents the different stakeholders involved in the project and, importantly, the relationships between them [69,70].

3.1.2.1.2 Risk classification taxonomy

Risk factors in onshore wind farm projects can be classified into a number of risk categories. The risk factor classification taxonomy developed here, and as illustrated in Fig. 4, was adopted from the generic taxonomy for risk factors in construction projects proposed by Siraj and Fayek [19]. Risk factors themselves are instances of the risk factor class and are linked to the risk classification class through a “hasType” relationship, as detailed in Section 3.1.2.2 below.

3.1.2.1.3 Project objectives taxonomy

The aim of all construction projects includes the execution of the project with a high level of quality, within planned budgets and schedules, with zero incidents, and with little, if any, harm to the environment [4]. When a risk factor occurs, it has the potential to impact one or more of these five objectives. As such, five sub-classes, namely cost, time, quality, safety, and environmental objectives, were included in the taxonomy of the project objectives class, as illustrated in Fig. 4.

3.1.2.1.4 Project work packages taxonomy

In certain conditions, risk factors are known to affect select portions of the project. Based on the work breakdown structures of onshore wind farm projects developed by Hao et al. [64] and Mohamed et al. [13], the construction activities of onshore wind farm projects were represented in the current ontology by eight primary work package sub-classes, as shown in Fig. 4.

3.1.2.1.5 Risk response strategy taxonomy

Risk response strategies in construction projects are commonly-grouped under five categories [71]. Accordingly, risk acceptance, risk elimination, risk transfer, risk retention, and risk reduction sub-classes for the risk response strategy class were developed in the ontology, as shown in Fig. 4.

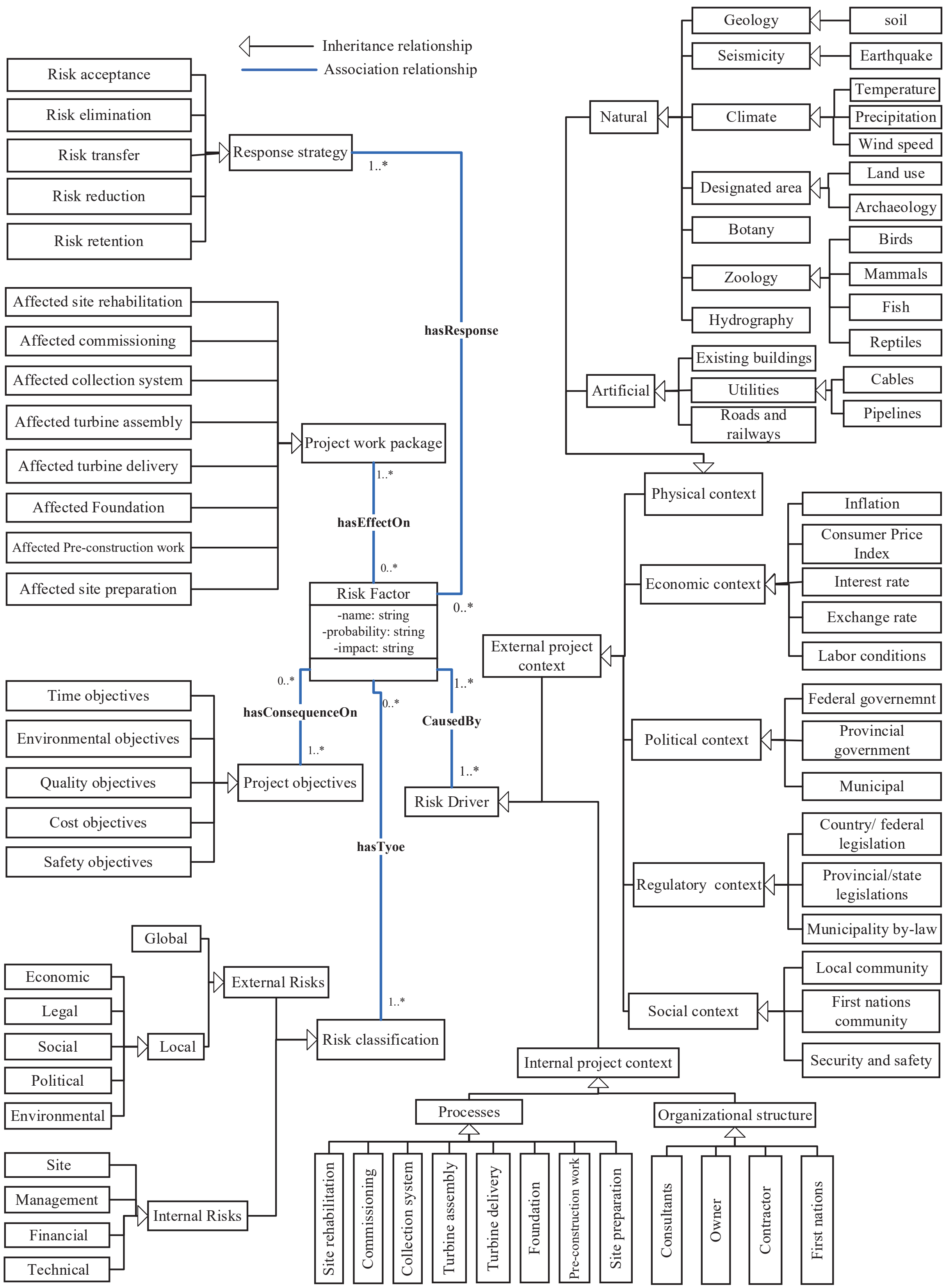

Fig. 4. An abstract UML class diagram of the risk ontology classes.

3.1.2.2 Relationship establishment

Semantic relationships emulate how two or more concepts are associated [9]. Relationships are often defined by a verb-containing phrase that describes the semantics of the relationship [9] to enable their reasoning [36]. Two of the five methods proposed by El-Diraby et al. [51] were applied to identify relationships in the current ontology, specifically (1) a review of related ontologies and their approaches to build relationships, and (2) expert review during the development phase of the research. All of the relationships defined between classes, in addition to the domain and range for each, are illustrated in Table 3 and Fig. 4. Details of this process are described as follows.

In the present research, relationships between classes and associated sub-classes were established using Hyponym–Hyperonym relationships. Hyponym–Hyperonym relationships, which have been referred to by a number of alternate terms including IS-A (is-a), a-kind-of, genus-species, and class-subclass relationships, are commonly-used to establish relationships [72]. Here, classes (i.e., hyperonyms) are related to sub-classes (i.e., hyponyms) using verb-containing phrases. For example, the risk drivers are divided into internal and external risk drivers, thus "internal risk drivers are a-kind-of risk drivers". Cause-and-effect relationships between concepts were described by a number of causative verbs, such as Cause, hasConsequenceOn, hasEffectOn, hasType, and hasResponse (as shown in Table 3 and Fig. 4). For example, "risk drivers cause risk factors". Finally, concept-object relationships were used to specify relationships between classes and their instances as, for example, "accidental damage of archaeological finds is-instance-of risk factor".

Table 3: Identified object properties between classes

No.	Domain	Object Properties (Relationship)	Range
1	Risk Factor	hasResponse	Response strategy
2	Risk Factor	hasEffectOn	Project work-package
3	Risk Factor	hasType	Risk Classification
4	Risk Factor	hasConsequenceOn	Project Objective
5	Risk Driver	Cause	Risk Factor
	Risk Factor	CausedBy	Risk Driver
6	Risk factor	OccuredIn	Project

3.1.2.3 Properties identification

Properties were used to represent the detailed characteristics of the predefined classes [63], as defined in Table 4. The inclusion of properties is particularly important for the project context class, as the associated risk factors depend on the specific characteristics (i.e., properties) of the project context.

3.1.2.4 Expert review of risk ontology

Once the class taxonomy, relationships, and properties were established, a second focus group meeting was organized to collect feedback from domain experts. Experts were asked to indicate whether or not they believed that the ontology was being developed in a manner that was representative of real operations and was capable of fulfilling the intended purpose. Each taxonomy was discussed in depth with the focus group, along with the associated relationships and properties. Questions that were asked in this meeting included, “Do you think the taxonomy depth comprehensively covers the knowledge in this class?”, “Do you think the relationships are logical and capture the association between classes?”, and “Is the hierarchy of the taxonomy reasonable?”.

3.1.3 Ontology implementation

Following the review by domain experts, the ontology was modeled using a knowledge-domain modeling platform to transform the ontology from a conceptual model to an implementable format for testing and application. Designed to facilitate the development, navigation, and visualization of knowledge-domain models, the free, widely used, and open-source ontology platform, Protégé, was applied to implement the risk identification ontology in the present study [73]. Notably, other ontology platforms may also be used.

Table 4. Data properties defined for the risk driver class.

Class (Domain)	Data Property	Data Type	Units
Project	Project name	String	–
	Project location	String	–
	Project size	Float	MW
	Project duration	Float	months
Roads and railways	Road category	String	–
	Average daily traffic	Float	vehicle/day
Existing buildings	Heritage significance	Boolean	–
	Closest construction activity	String	–
	Distance to closest activity	Float	m
Utilities (pipelines/cables)	Closest construction activity	String	–
	Distance to closest activity	Float	m
Botany	Name	String	–
	Closest construction activity	String	–
	Distance to closest activity	Float	m
Temperature	Min. winter temperature (5-yr. avg.)	Float	°C
	Max. winter temperature (5-yr. avg.)	Float	°C
	Average winter temperature (5-yr. avg.)	Float	°C
Precipitation	Average snowfall (5-yr. avg.)	Float	cm
	Maximum snowfall (5-yr. avg.)	Float	cm
	Average rainfall (5-yr. avg.)	Float	mm
	Maximum rainfall (5-yr. avg.)	Float	mm
Wind	Maximum wind speed (5-yr. avg.)	Float	m/s
	Average wind speed (5-yr. avg.)	Float	m/s
Archaeological heritage	Closest construction activity	String	–
	Distance to closest activity	Float	m
	Heritage significance	Boolean	–
Land use	Purpose	String	
	Affected area size	Float	m^2
Soil	Type	String	–
	Groundwater level	Float	m
Hydrography	Closest construction activity	String	–
	Distance to closest activity	Float	m
Earthquake	Return period	Integer	years

	Magnitude	Float	Richter
Zoology	Closest construction activity	String	–
	Distance to closest activity	Float	m
	Breed in the area	Boolean	–
	Animal name	String	–
Political	Overall stability	Boolean	–
	Support for the project	Boolean	–
Regulatory	Responsible agency	String	–
	Approval status	Boolean	–
Social	Attitude toward project	String	–
	Participation in public consultation	Boolean	–
Organizational	Cooperation level	String	–
	Risk attitude	String	–
	Clear responsibility	Boolean	–
Response strategy	Description	String	–
Risk factor	Probability	String	–
	Impact	String	–

3.1.4 Ontology verification

Two evaluation methods were used in the present study to verify the implementable version of the risk ontology. First, an automated consistency check was applied to ensure that the ontology was free from contradicting facts [74], which can result in inconsistencies and, ultimately, in incorrect conclusions. Second, criteria-based evaluation was used to verify the content of the ontology using a predefined set of criteria proposed for ontology evaluation in previous research [7,9]. The verification processes are detailed as follows.

3.1.4.1 Automated consistency check

The Pellet reasoner [75] in Protégé was used to perform an automated consistency check for inconsistent and disjointed class assertions, domains, and ranges of relationships. Results of the final consistency check are shown in Fig. 5, indicating that inconsistencies were not found.

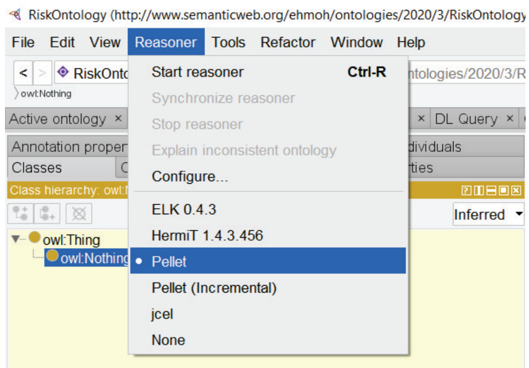

Fig. 5. Consistency check in Protégé.

3.1.4.2 Criteria-based evaluation

Criteria-based evaluation was conducted through interviews with domain experts using a focus group approach. Experts were selected based on the following criteria: (1) years of experience in the risk management of construction projects, and (2) familiarity with risk identification in wind farm projects. To reduce bias, experts that did not participate in the ontology development review process performed the evaluation. Three experts, namely a project manager, estimator, and risk analyst, with an average of 15 years of experience in industry were selected.

The goal of the criteria-based evaluation was to test the adequacy of the semantics and the ease of use of the ontology [55]. Once selected, experts were asked to rate their satisfaction with the proposed risk ontology across several criteria using a 5-point Likert scale. An open-ended question asking the experts to indicate other areas of the ontology that may require further investigation was also included. Results of the criteria-based evaluation are summarized in Table 5 and are described below.

Table 5. Overall evaluation by experts.

Criteria	Sub-Criteria	Average	Std. Dev.
Coverage	Core concepts are incorporated	4.33	0.57
	All relationships are incorporated	4.00	1.00
Completeness	Definitions of classes, taxonomy, and relationships are complete	4.33	0.57
	The ontology explicitly includes all that should be included	4.67	0.57
Clarity	All concepts in the ontology are clear	5.00	0
	Concepts are in agreement with literature	4.33	0.57
Conciseness	Ontology does not contain unnecessary concepts	4.67	0.57
	Ontology does not contain explicit redundancy between concepts	5.00	0

3.1.4.2.1 Coverage

Coverage assesses whether the ontology incorporates the main concepts and relationships within the domain or lacks certain classes and relationships [63]. This criterion was also examined throughout the conceptual formulation stage as the taxonomies and relationships of the schema of the domain model were established. Based on the results of the evaluation, subject experts "agreed" that core concepts and all relationships are incorporated in the developed wind farm risk ontology. The overall average evaluation of this criterion was 4.16 (Table 5), with a standard deviation of less than one, indicating that the evaluation was consistent amongst the experts. The experts proposed that other concepts could be added to benefit the risk quantification stage.

- Completeness

Completeness determines if the classes, taxonomies, and relationships defined in the ontology are complete and appropriate for use in the application stage [74]. The ontology is considered adequate to support specific data needs if two conditions are satisfied: (1) each definition is complete, and (2) the ontology explicitly includes all that should be included [74].

To achieve this, a top-down approach is used to assess if each top class is complete with respect to its sub-classes (taxonomy) and if the domain and range for each relationship is defined. The overall average evaluation of this criterion was 4.50 (Table 5), indicating that the experts "agreed to strongly-agreed" that the classes, taxonomies, domain, and range of the relationships were complete. There were no open-ended comments regarding completeness.

- Clarity

Clarity of ontology indicates if an ontology can clearly exhibit the intended meanings of the developed classes and their taxonomies without ambiguity. This criterion was also examined throughout the conceptualization stage as concepts and standards for defining and setting the meaning of each concept/class were extracted from literature. The clarity criterion was evaluated based on the two items: (1) concepts are clear, and (2) intended concept definition was consistent with definitions from literature and practice. The overall average evaluation of this criterion was 4.67 (Table 5), indicating that the experts "agreed to strongly-agreed" that all concepts and their intended meanings were consistent with definitions from literature and practice. There were no open-ended comments regarding clarity.

- Conciseness

Conciseness assesses if the information collected in the ontology is useful and precise [74]. Gómez-Pérez [74] indicated that an ontology is concise if the following two conditions are met: (1) it does not contain unnecessary and useless concepts, and (2) explicit redundancy does not exist between concepts. The overall average evaluation of this criterion was 4.84 (Table 5), indicating that the experts "agreed to strongly-agreed" that the ontology did not contain redundancies or unnecessary concepts. There were no open-ended comments regarding conciseness.

3.2 Proposed framework

After development, the domain-specific risk ontology was integrated into the proposed framework. Application of the framework involves three primary steps: (1) ontology population, (2) current project data collection and input, and (3) risk factor identification, as shown in Fig. 1.

3.2.1 Ontology population

Historical data of previous projects are input into the domain-specific risk ontology to establish instances of each class in a process known as a ontology population or instance extraction [76,77]. The contextual information of previous historical projects, together with the risk information of these projects, are then used to extract the instances of the developed risk ontology. Instance extraction can be performed either manually or using certain automated information extraction frameworks [76,77]. Enriching the contextual information of the ontology is expected to improve risk identification in future projects. Thus, once constructed, project data should be populated into the ontology as new instances.

3.2.2 Current project data collection

After inserting the instances into related classes, the ontology—now enriched with knowledge—can be used to fetch information for risk identification purposes. It is important to note that if project data are confidential and should not be published publicly, instances' data and the ontology should be stored in separate repositories to ensure data security and then these separate repositories can be queried. Current project data are then input into the populated ontology. Required inputs for this process include the contextual information about the project for which risk factors must be identified. This information can be collected once the context of the project is established (i.e., scope of the project and surrounding environment) from various project documents, such as construction plan reports, financial reports, built heritage assessments, and environmental assessments. Examples of input data collection are described in Section 4.2 of the case study.

3.2.3 Risk factor identification

Once the current project data are collected, the contextual information is fed, using queries, into the ontology. The queries that input the contextual project information are responsible for fetching and retrieving context-specific project risk factors for the project under study. The ontology can be accessed through a standard query language, which uses a standard code (e.g., Python, C#) and a triple store/graph database (e.g., ontotext graphdb, etc.) to fetch and identify context-based information. One common standard query language is the Standard Protocol and RDF Query Language (SPARQL), which is used to query graph data represented as RDF triples [78]. Also, A Decision Logic (DL) query is a class expression that uses a user-friendly syntax for OWL DL constructed using constructs such as ‘and’ and ‘some’ to collect information about a particular class, property, or individual [79]. The DL query language, supported by a user-friendly syntax plug-in for OWL DL, is designed to collect all information about a particular class, property, or individual [79]. SPARQL queries, in contrast, have greater flexibility and applicability than DL queries. Readers are referred to the online SPARQL reference site [78] for a detailed explanation of SPARQL queries. Various risk-related information can be retrieved based on the structures of the queries and descriptors of the project context. Examples of these queries are presented in Section 4.3.

Once risk factors for the new project have been identified, risks can be further analyzed by determining their impacts, probabilities, and proposing appropriate response strategies. Risk management literature includes a large body of work; readers are referred to the work of Somi et al. [2], Mohamed et al. [13], and Mohamed et al. [80] for a review of current risk management approaches in onshore wind farm construction.

4. Case study

Publicly-available data from seven real wind farm projects were used to demonstrate the functionality and applicability of the proposed framework. The onshore wind project, Settlers Landing [81], was chosen as the study project to which the proposed risk identification framework was applied. Historical projects used to develop the class instance representations and populate the ontology are listed in Table 6. Protégé, a free, widely used, and open-source ontology platform, was used to implement the risk identification ontology. The reader is referred to the user guide [82] of Protégé for a detailed overview of the development steps.

4.1 Ontology population

A dataset of six onshore wind farm projects located in Ontario, Canada, was collected and used to fill and build the instances of the proposed ontology. A description of these projects is provided in Table 6; all are onshore wind farms. Project documents that were available included project descriptions, construction plans, cultural heritage assessments, natural heritage assessments, and noise assessments.

Instances for each class were extracted from these documents, including the risk factors, context of the project (i.e., risk drivers), risk response strategies, and attributes of the instances. Public disclosure of project documents is often limited to risks pertinent to the public. As such, the majority of extracted information was related to environmental or social risk factors. These included environmental risk factors with the potential to cause damage or harm to the surrounding environment of the projects, or social risk factors such as traffic congestion and noise disturbances due to construction activities. A manual instance representation approach was adopted in the current case study. First, related documents from different sources were reviewed; then, instances were extracted and input into the related class in the ontology. Historical risk knowledge was implemented and coded in Protégé platform [83], as shown in Fig. 6. The extracted risk concepts and taxonomies were modeled as “classes” (Fig. 6; red box); relationships between concepts were modeled as “object properties” (Fig. 6; blue box); and attributes of the classes were modeled as “data properties” (Fig. 6; green box).

Table 6. Details of the projects used for class instance representation.

No.	Project	Project Size (MW)	No. of Risk Factors
1	Belle River Wind Project [84]	73.5	8
2	Bornish Wind Energy Centre [85]	72.9	8
3	Grey Highlands Clean Energy [86]	18.5	7
4	Grey Highlands Zero Emission [87]	10.0	6
5	K2 Wind Project [88]	270	6
6	Port Ryerse Wind Power [89]	10.0	4

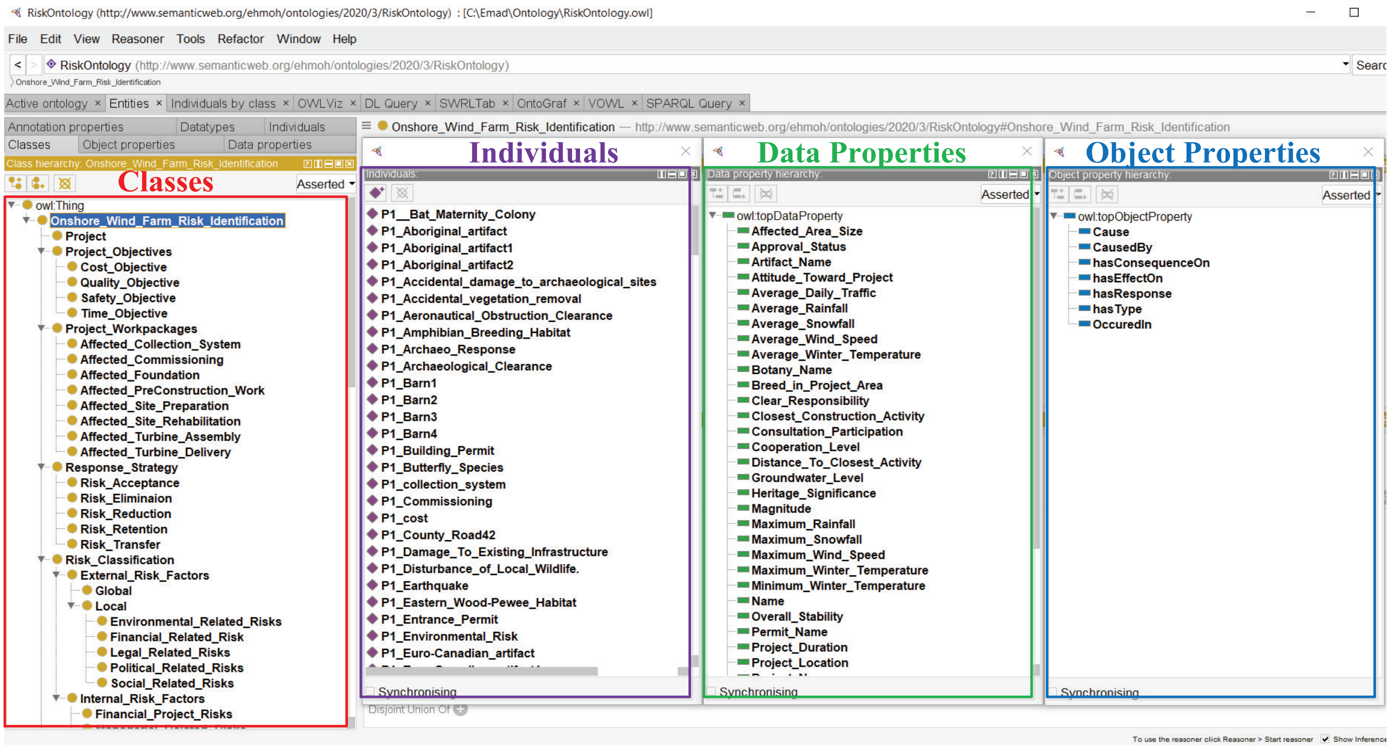

Fig. 6. Screenshot of the risk ontology in Protégé.

Examples of the populated instances for one risk factor, as well as an example of populated instances of the risk factors for an entire project are provided as Figures 8 and 9, respectively. The semantic structure of the risk factor "Accidental Damage of Archaeological Finds" from the Belle River Wind Project is shown in Fig. 7. This risk factor has six drivers (CausedBy, Cause), which are the foundation excavation activity and the presence of five archaeological artefacts near the construction activities. This risk factor is classified (hasType) as an environmental risk factor (P1_Environmental_Risk) and is an instance of the class "Risk_Factor". This risk factor can impact (hasConsequenceOn) the project time objective (P1_time) because regulations require that work must stop immediately. This risk factor occurred in (OccuredIn) the Belle River Wind Project, or Project 1. The attributes of the archaeological finds in the project study area are provided in Table 7. The example provided in Fig. 7 illustrates the advantages of using ontologies to model risk information, specifically (1) the ability to model information at the risk-level precisely, and (2) the elegance and simplicity of the resulting visualization.

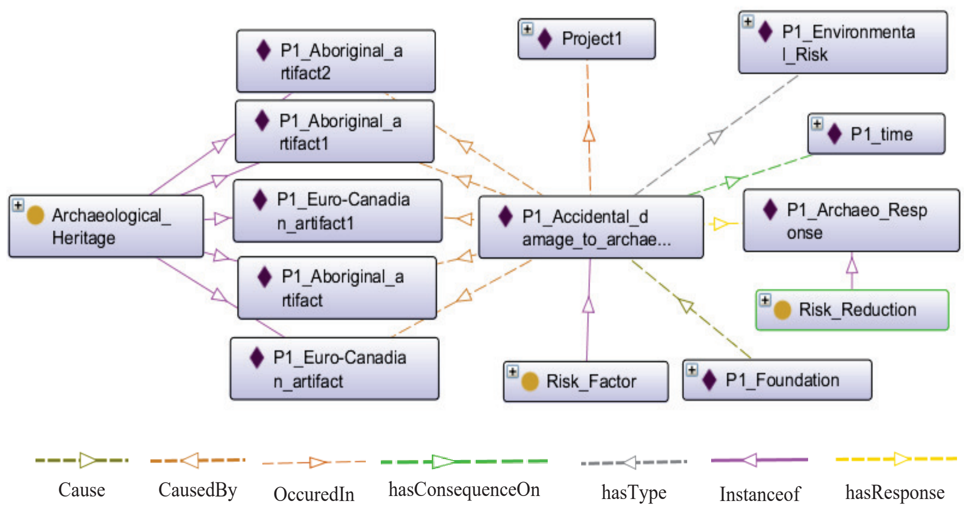

Fig. 7. Semantic structure of archaeological damage risk in Protégé.

Table 7. Data properties of archaeological finds.

Artifact Name	Closest Activity	Distance to Activity (m)	Heritage Significance
Aboriginal Artifact	Turbine 1	200	Yes
Aboriginal Artifact 1	Turbine 2	285	Yes
Aboriginal Artifact 2	Turbine 3	30	Yes
Euro-Canadian Artifact	Turbine 1	131	Yes
Euro-Canadian Artifact 1	Turbine 3	140	Yes

All remaining risk factors in the Belle River Wind Project were modeled and implemented using an approach similar to the detailed risk example. Fig. 8 illustrates the semantic structure, risk drivers (context), and the response strategies of the eight risk factors identified in Project 1. The other five projects were modeled and added to Protégé using a similar approach.

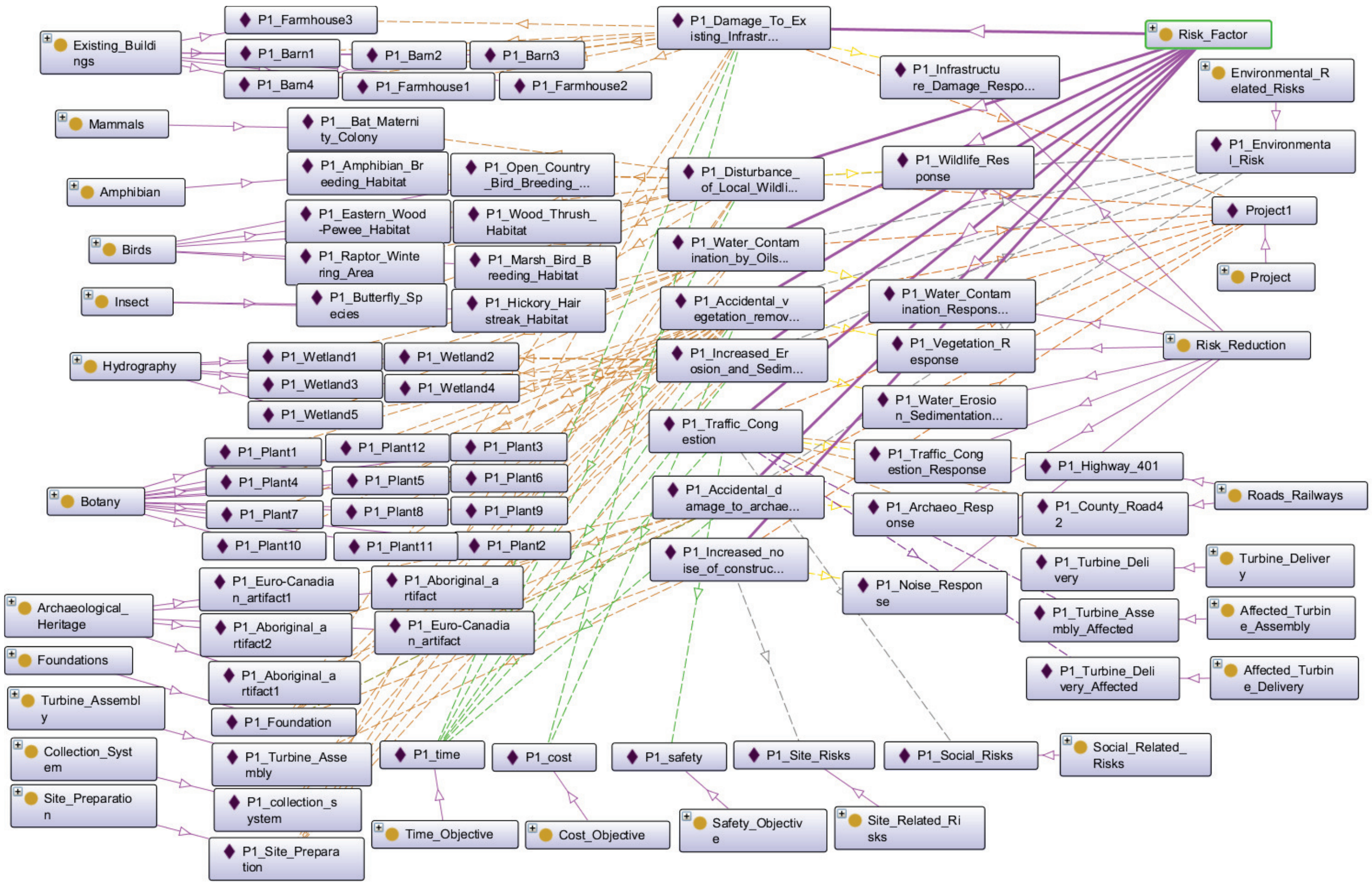

Fig. 8. Semantic structure of Project 1 risk factors along with their context in Protégé.

4.2 Current project data collection

Then, contextual project information from the project under study (i.e., risk identification project) was collected and prepared for input into the ontology. Information was retrieved from project data available in the Settlers Landing project repository [81] and summarized as shown in Table 8.

Table 8. Project context information.

Item	Class	Data Property (Attributes)	Data Value	Unit
New wind project	Project	Project name	Project A	–
		Project location	Ontario, Canada	–
		Project size	8	MW
		Project duration	5	months
Stone farmhouse	Existing buildings	Heritage significance	Yes	–
		Closest construction activity	Access Road	–
		Distance to closest activity	750	m
Plant 1	Botany	Name	Sugar Maple	–
		Closest construction activity	Turbine 3	–
		Distance to closest activity	33	m
Plant 2	Botany	Name	White Oak	–
		Closest construction activity	Turbine 3	–
		Distance to closest activity	33	m
Plant 3	Botany	Name	White Birch	–
		Closest construction activity	Turbine 3	–
		Distance to closest activity	33	m
Amphibian 1	Amphibian	Animal name	Amphibian Breed. Habitat	–
		Closest construction activity	Underground Cable	–
		Distance to closest activity	230	m
		Breed in the area	Yes	–
Reptile 1	Reptiles	Animal name	Snake Hibernacula	
		Closest construction activity	Underground Cable	–
		Distance to closest activity	46	m
		Breed in the area	Yes	–
Mammal 1	Mammals	Animal name	Bat Maternity Colony	–
		Closest construction activity	Access Road	–
		Distance to closest activity	18	m
		Breed in the area	Yes	–

4.3 *Risk factor identification*

Seven separate SPARQL queries were designed for each of the defined project contexts provided in Table 8. Queries were directly expressed and written in the separate SPARQL tab in Protégé. The query itself was written in the top part of the tab, while query results were displayed in the bottom portion of the tab as shown in Fig. 9, Fig. 10, and Fig. 11. Query 1 extracted the risk factors and their response strategies that could be implemented to mitigate risks resulting from the presence of existing buildings surrounding the project. The results of the query are shown in Fig. 9. Here, one risk factor, "Damage to Existing Infrastructure" was identified and recalled based on the similarity of the current project (i.e., Settlers Landing) to historical Project 1. Project 1 (i.e., Belle River) had three existing buildings (Farmhouses 1-3) located within the project area within varying distances of construction activity. Using the context of the current project, which also is characterized by the presence of a farmhouse, the framework was able to automatically recall and identify the risk factor "Damage to Existing Infrastructure" as well as the associated response strategies.

Query 2 was designed to fetch and retrieve instance data for risk factors associated with the existence of sugar maple trees in the project area based on the contextual information specified in Table 8. Fig. 10 shows the results of the query. Here, two risk factors "Accidental Vegetation Damage/Removal" were recalled from Projects 2 and 5 based on their contextual similarity to the current project (i.e., Settlers Landing).

SPARQL query:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX : <http://www.semanticweb.org/ehmoh/ontologies/2020/3/RiskOntology#>

 SELECT ?Risk  ?Project  ?Driver ?Sig ?Distance  ?Activity ?Description
                                        WHERE {
                                                ?Risk a :Risk_Factor .
                                                ?Risk :OccuredIn ?Project .
                                                ?Risk :CausedBy ?Driver .
                                                ?Risk :hasResponse ?Response .
                                                ?Response :Response_Description ?Description.
                                                ?Driver a :Existing_Buildings .
                                                ?Driver :Heritage_Significance ?Sig .
                                                ?Driver :Distance_To_Closest_Activity ?Distance .
                                                ?Driver :Closest_Construction_Activity ?Activity .
                                                FILTER regex(str(?Activity), "road") .
                                                FILTER regex(str(?Driver), "house") .
                                                FILTER (?Distance < "750"^^xsd:float)
                                                }
```

Risk	Project	Driver	Sig	Distance	Activity	Description
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse1	"true"^^	"50.0"^^<	"access road"	"Install a 20 m protective buffer zone to avoid these sites"^^<http://www.w3.org/2001/XMLSchema#string>
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse1	"true"^^	"50.0"^^<	"access road"	"Adhere to best practices regarding the operation of construction equipment and delivery of construction materials."^^<h
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse1	"true"^^	"50.0"^^<	"access road"	"No ground alteration activities will take place inside of the 20 m protective zone"^^<http://www.w3.org/2001/XMLSchema#
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse3	"true"^^	"40.0"^^<	"access road"	"Install a 20 m protective buffer zone to avoid these sites"^^<http://www.w3.org/2001/XMLSchema#string>
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse3	"true"^^	"40.0"^^<	"access road"	"Adhere to best practices regarding the operation of construction equipment and delivery of construction materials."^^<h
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse3	"true"^^	"40.0"^^<	"access road"	"No ground alteration activities will take place inside of the 20 m protective zone"^^<http://www.w3.org/2001/XMLSchema#
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse2	"true"^^	"50.0"^^<	"access road"	"Install a 20 m protective buffer zone to avoid these sites"^^<http://www.w3.org/2001/XMLSchema#string>
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse2	"true"^^	"50.0"^^<	"access road"	"Adhere to best practices regarding the operation of construction equipment and delivery of construction materials."^^<h
P1_Damage_To_Existing_Infrastructure	Project1	P1_Farmhouse2	"true"^^	"50.0"^^<	"access road"	"No ground alteration activities will take place inside of the 20 m protective zone"^^<http://www.w3.org/2001/XMLSchema#

Fig. 9. SPARQL query of existing buildings related risk factors.

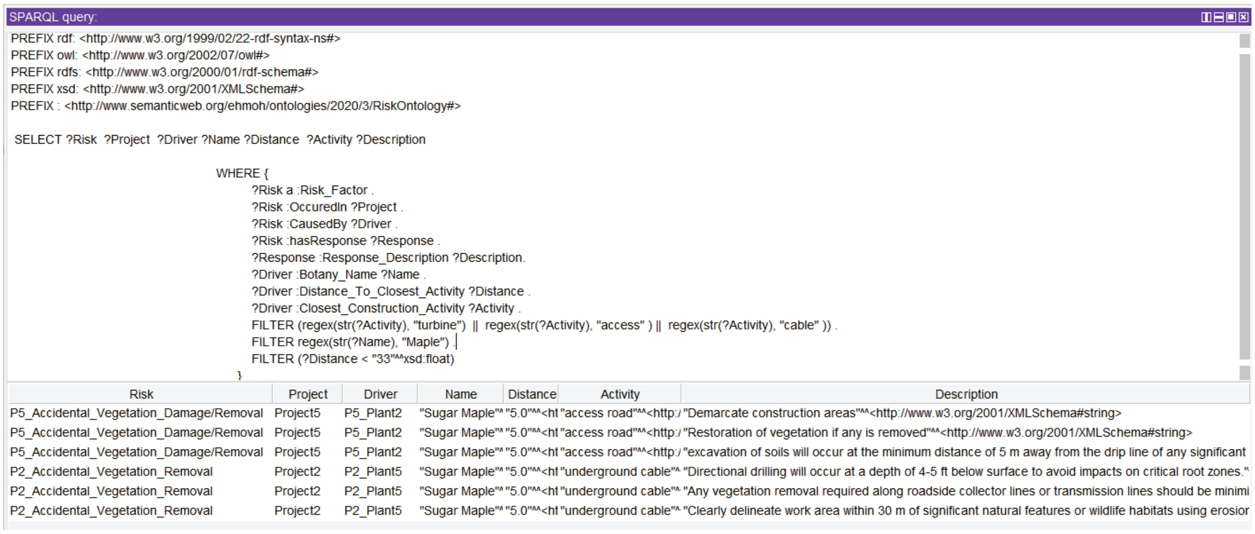

Fig. 10. SPARQL query of risks related to sugar maple trees.

Similarly, Queries 3 and 4 were designed to identify risks associated with white oak and white birch trees in the project area by entering the associated contextual information (e.g., botany name, closest construction activity, and the distance to the closest activity) into the query. Queries 5 through 7 were also developed to identify risk factors resulting from the existence of amphibians, snakes, and bats. Implementation of Query 5 is illustrated in Fig. 11. Queries 6 and 7 were implemented using a similar approach, with the animal name, closest construction activity, and distance to activity changed as applicable. The six risk factors recalled and identified using the proposed framework for the construction of the Settlers Landing onshore wind project are detailed in Table 9.

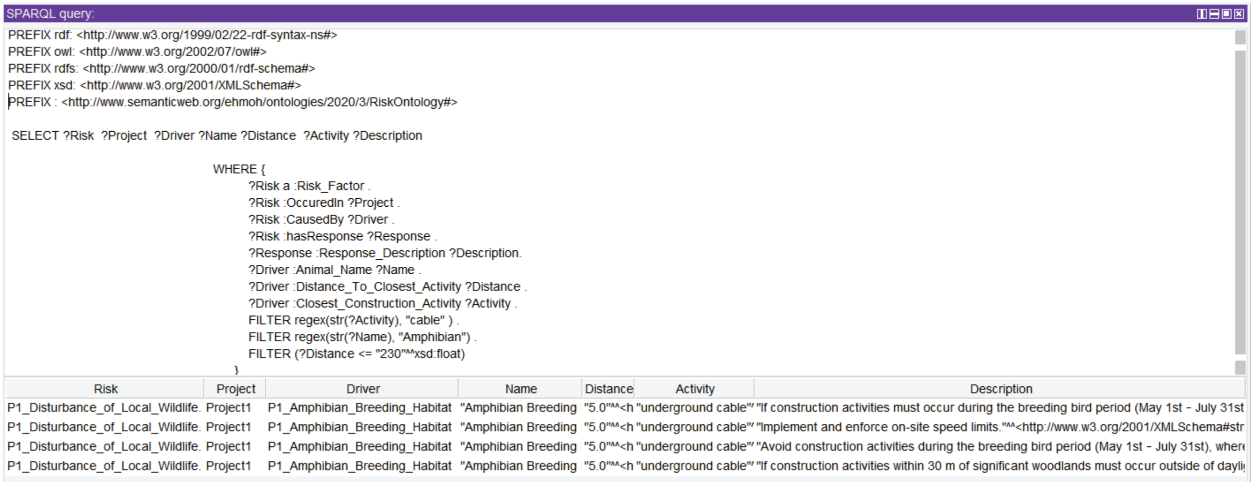

Fig. 11. SPARQL query of amphibian related risks.

Table 9. Identified risks of the Settlers Landing wind project during construction.

No.	Risk Factors	Retrieved from	Response Description
1	Damage to existing buildings	Project1	• Install a 20 m protective buffer zone to avoid these sites • No ground alteration activities will take place inside of the 20 m protective zone • Adhere to best practices regarding the operation of construction equipment and delivery of construction materials
2	Accidental damage to sugar maple trees	Projects 2 and 5	• Directional drilling will occur at a depth of 4-5 ft. below surface to avoid impacts on critical root zones • Any vegetation removal required along roadside collector lines or transmission lines should be minimized and occur completely within the road right-of-way • Clearly delineate work area within 30 m of significant natural features or wildlife habitats using erosion fencing, or similar barrier, to avoid accidental damage to species to be retained • Demarcate construction areas • Restoration of vegetation if any is removed • Excavation of soils will occur at the minimum distance of 5 m away from the drip line of any significant woodland
3	Accidental damage to white birch trees	Project 5	• Excavation of soils will occur at the minimum distance of 5 m away from the drip line of any significant woodland • Restoration of vegetation if any is removed • Demarcate construction areas
4	Accidental damage/mortality of amphibians	Project 1	• If construction activities must occur during the bird breeding period (May 1–July 31), a biologist will conduct nest searches, in areas where natural vegetation will be removed, to ensure there will be no impact to breeding birds • Implement and enforce on-site speed limits • If construction activities within 30 m of significant woodlands must occur outside of daylight hours, spotlights will be directed downward and/or away from the woodland to limit potential light disturbance to breeding birds

5	Mortality of snake and damage of hibernaculum	Project 3	• Construction personnel will be educated about the location and significance of these features • Flag and demarcate the 30 m area around each hibernaculum
6	Disturbance and/or mortality of bat	Project 2	• Propose a lighting scheme to that will minimize potential risk to bat collisions while fulfilling Transport Canada requirements • Clearly delineate work area using erosion fencing, or similar barrier, to avoid accidental damage to potentially significant bat roosting trees

4.4 *Framework evaluation and anticipated benefits*

The risk factors identified by the proposed framework (Table 9) were compared with risks extracted from the publicly-available project documentation on which the case study was based [81]. All of the risk factors discussed in the documentation were successfully identified by the proposed framework, demonstrating the ability of the proposed framework to generate comprehensive, representative results in shorter duration.

The proposed framework was compared to previous risk identification techniques. This comparison was completed by the authors. Differences and advantages to using the ontology-based approach are summarized in Table 10.

Table 10. Comparison of the ontology-based approach with previous risk identification techniques.

Item	Risk Identification Technique							
	Delphi technique	Brainstorming	Interviews	Checklists	Risk register	Rule-based system [70]	Case-based reasoning [2]	Current study (ontology-based approach)
Reliance on manual review of prior project data	✓	✓	✓	✓	✓	x	x	x
Automatically maps the project contextual information to risk information	x	x	x	x	x	x	x	✓
Consideration of detailed contextual information of the project	x	x	x	x	x	✓	x	✓
Require intensive time and effort	✓	✓	✓	✓	✓	✓	✓	x

To perform traditional risk identification, a risk analyst would have needed to review project documents for four historical projects with similar contexts and review the documents for the project under study. This laborious process was easily and rapidly performed using the proposed framework once the new project context is determined. Traditional risk identification techniques lack the capability to map contextual project information to risk factors. The risk analysts, therefore, are required to manually screen and identify which risk factors are relevant to the new project. Although the rule-based system [70] does not require a manual review of project documents and, instead, considers detailed contextual project information, the risk analyst is still required to define a lengthy list of if-then rules to map the contextual project information to risk factor information for reasoning and identifying related risk factors. The ontology-based approach proposed in this study eliminated the need for these if-then rules because the contextual and risk information is already mapped and linked through the object properties. The framework was also compared to the fuzzy case-based reasoning method for risk identification in onshore wind projects proposed by Somi et al. [2,43]. The case-based reasoning approach makes use of two project characteristics—project type and project work packages—to retrieve similar projects. All risk factors in similar projects are then extracted based on the calculated similarity between the two projects without screening. The last step in case-based reasoning risk identification is that a risk analyst must screen the risk factors and determine which risks should apply to the project under study. Notably, the fuzzy case-based reasoning approach could not consider and model the detailed project context in addition to other risk factors information such as the response strategies and risk drivers—a major advantage of the proposed methodology. The ontology-based approach proposed in this study extracts the risk factors simultaneously based on the detailed contextual information that is used in reasoning about the risk factors.

Risk ontology represents a unified knowledgebase of risk information where risk analysts can share and use concepts and terminologies related to risk factors, project context, and response strategies. The benefits of considering project context and contextual information during risk identification were demonstrated in the case study presented here. The incorporation of detailed contextual project information and risk factor information in one semantic model capable of automatically reasoning and identifying risk factors considerably reduces the effort and time required to identify risk factors for a new project when compared to previous models. Furthermore, the ability of the ontology to identify risk factors based on historical information rather than expert recall is anticipated to increase the accuracy of risk identification results, thereby improving risk management efforts for both current and future projects.

5. Discussion

Risk identification for onshore wind farm projects is a burdensome task for risk analysts in construction companies because (1) risk factors have multi-source drivers that must be defined accurately [70], (2) information related to risk factors, risk drivers, and response strategies are fragmented across various documents, increasing the time and effort required to review these documents [4], and (3) for the information to be useful in future projects, data related to the risk factors must be saved in a manner that can be easily shared and reused. Indeed, as the risk knowledge maintained by risk analysts increases, so too does the accuracy of risk identification processes. The risk ontology will also facilitate the development of a unified understanding among engineers of the risks and related concepts, increasing the consistency of risk knowledge between new and old projects and across company teams.

Current risk identification practice still relies on spreadsheets and text documents, limiting the communication of risk knowledge in practice. A knowledge model that can overcome these challenges can represent a real benefit to risk experts and analysts. Ontology and semantic web technology have been applied successfully to solve a wide range of knowledge modeling problems. Building on these findings, an ontology-based approach to address existing risk identification knowledge limitations was developed. The ontology was evaluated by domain experts who agreed with the validity and practicality of the model.

Although there will be similarity between classes across different construction projects when developing risk ontology for strategic project-level risk identification, certain classes will differ from one project to another. Onshore wind projects are a unique type of construction project that are characterized by repetitive construction, as each project has several turbines that are constructed in a similar way. This uniqueness of onshore wind projects was considered while developing the risk ontology: two classes were specifically designed for this type of project, namely the "Processes" class and the "Project work package" class as shown in Fig. 4. These two classes will differ from one project type to another depending on the project work breakdown structure. The reader should consider this distinction when developing risk ontologies for different project types.

The following limitations should be considered in parallel with the findings of the study. First, the ontology model was developed based on project data from the Canadian wind energy sector. While it is expected that the model can be successfully applied to any onshore wind project using the proposed methodology, the adaptability of the approach was not directly tested in the present study. Second, the quality of output results is highly dependent on the quality of the input data. In the case study, risk factors related to the presence of white oak trees in the project area were not detected, as similar contexts were not identified within the five historical projects used to populate the ontology. Third, with the current development, the ontology included only risk knowledge related to environmental risk factors, which was the only information accessible in publicly-available project documents. In practice, however, there is no limit to the amount of information that construction companies can input (i.e., as instances) to enrich the ontology. In the future, the onshore risk knowledge stored in the model should be expanded. Application of the framework to additional onshore wind farm projects will assist in further validating the model. Future work can also focus on the development of methods capable of automating ontology population and insertion of instances.

6. Conclusion

Risk identification is an important yet challenging task. While unidentified risks must be identified, analyzed, and managed, the abundance of fragmented information that must be considered for risk identification renders this process time-consuming, prone-to-error, and challenging. Accordingly, this research has developed an ontology-based approach to overcome limitations in the risk identification process. Identification-related information—which includes risk factors, risk drivers, risk response strategies, consequence on project objectives, and effect on project work packages—are modeled semantically using ontologies. The proposed approach was validated using an automated consistency check, criteria-based evaluation, and application-based evaluation of a real project. The evaluation demonstrated that the proposed methodology was beneficial and valuable for risk identification in onshore wind farm projects by decreasing the burden on risk analysts. Risk analysts can use the proposed ontology-based approach to easily and accurately save, communicate, and reuse the knowledge required for risk identification. Reuse of the ontology also allows identification of context-based risk factors when a new project is defined.

ACKNOWLEDGMENTS

This work was supported by Future Energy Systems as part of the Canada First Research Excellent Fund (CFREF FES-T11-P01). Part of this work was performed using the Protégé resource, which is supported by grant GM10331601 from the National Institute of General Medical Sciences of the United States National Institutes of Health.

Appendix A

Table A.1. Competency questions formulated in Query format.

CQ	CQ answer	SPARQL Query
What is (are) the purpose(s) of the ontology?	The purpose of this risk ontology is to identify the context-driven strategic project-level risk factors that affect project objectives, that have specific drivers, thathave response strategies, and thatoccurred in similar context of previous wind projects where the project size is less than 20 megawatts.	SELECT ?Risk ?Driver ?Project ?ProjectSize ?Response ?Description WHERE { ?Risk a :Risk_Factor . ?Risk :CausedBy ?Driver . ?Risk :OccuredIn :Project_ID. ?Project :Project_Size ?ProjectSize . ?Risk :hasResponse ?Response . ?Response :Response_Description ?Description. FILTER (?ProjectSize < "20"^^xsd:float)}
What parts of the risk management process should be covered by the ontology?	The risk ontology is focused on the risk identification stage of the risk management process. Other stages of risk management process, such as risk quantification, are not part of the risk ontology. For example, the shown query.	SELECT Distinct ?individual ?class WHERE { ?individual a :Risk_Factor . ?individual rdf:type ?class .}
How risk factors will be identified?	A context-based approach will be used to identify the risk factors where information about the project will be used to retrieve risk factors information from previous projects. Thus, the concept of risk drivers will be used to represent contextual risk information.	SELECT ?Risk ?Driver ?Name WHERE { ?Risk a :Risk_Factor . ?Risk :CausedBy ?Driver . ?Driver :Driver_Name ?Name }

What types of risks should be included?	Different types of risks should be included in the ontology, including internal project risks and external project risks. Internal risks include technical, financial, managerial, and site-related risks. External risks include social, economic, legal, political, and environmental-related risks.	SELECT ?Risk WHERE { ?Risk a :Risk_Factor . ?Risk : hasType :Financial_Risks. ?Risk :hasType :Management_Risks. ?Risk :hasType :Technical_Risks. ?Risk :hasType :Site_Risks. ?Risk :hasType :Social_Risks. ?Risk :hasType :Economic_Risks. ?Risk :hasType :Legal_Risks. ?Risk :hasType :Polotical_Risks. ?Risk :hasType :Environmental_Risks. ?Risk :hasType :Global_Risks}
What information should be captured in the ontology?	The risk ontology should contain all the information required for risk identification, including risk factors; the information of previous projects where these risks occurred, such as project name and size; risk drivers of the risk factors; response strategies taken for the risk factors; project objectives affected by the risk factors; and which project components may be affected by the risk factors.	SELECT ?Risk ?Project ?ProjectSize ?Driver ?Name ?Response ?Description WHERE { ?Risk a :Risk_Factor . ?Risk :OccuredIn ?Project . ?Risk :hasResponse ?Response . ?Response :Response_Description ?Description. ?Risk :hasConsequenceOn ?Objective . ?Objective :Objective_Name ?Name . ?Risk :CausedBy ?Driver . ?Driver :Driver_Name ?Name . ?Risk :hasEffectOn ?Project_Workpackage ?Project :Project_Size ?ProjectSize . FILTER (?ProjectSize < "100"^^xsd:float)}
What is needed to perform the risk identification processes?	The specific project information which represents the context of the project that will be used to retrieve risk factor information from similar previous projects. This information will be used in queries to extract the related risk information. For example, this query attempts to extract the risk factors that may occur due to the existence of buildings in the vicinity of access road construction activity.	SELECT ?Risk ?Project ?Driver ?Sig ?Distance ?Activity ?Description WHERE { ?Risk a :Risk_Factor . ?Risk :OccuredIn ?Project . ?Risk :CausedBy ?Driver . ?Risk :hasResponse ?Response . ?Response :Response_Description ?Description. ?Driver a :Existing_Buildings . ?Driver :Heritage_Significance ?Sig . ?Driver :Distance_To_Closest_Activity ?Distance . ?Driver :Closest_Construction_Activity ?Activity . FILTER regex(str(?Activity), "road") . FILTER regex(str(?Driver), "house") . FILTER (?Distance < "750"^^xsd:float)}
Who are the end-users of the ontology?	The risk ontology is intended to be used by project managers, risk analysts, and project engineers.	

REFERENCES

[1] IRENA, Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects (A Global Energy Transformation paper), International Renewable Energy Agency, Abu Dhabi, 2019. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Oct/IRENA_Future_of_wind_2019.pdf (accessed July 12, 2020).
[2] S. Somi, N. Gerami Seresht, A.R. Fayek, Framework for Risk Identification of Renewable Energy Projects Using Fuzzy Case-Based Reasoning, Sustainability. 12 (2020) 5231. https://doi.org/10.3390/su12135231.
[3] N. Gatzert, T. Kosub, Risks and risk management of renewable energy projects: The case of onshore and offshore wind parks, Renew. Sustain. Energy Rev. 60 (2016) 982–998. https://doi.org/10.1016/j.rser.2016.01.103.
[4] S. De Zoysa, A.D. Russell, Knowledge-based risk identification in infrastructure projects, Can. J. Civ. Eng. 30 (2003) 511–522. https://doi.org/10.1139/l03-001.
[5] L. Zhang, Y. Zhong, Engineering Research with Application of System Dynamics Model of Risk Identification in Railway Construction Project, Adv. Mater. Res. 977 (2014) 536–540. https://doi.org/10.4028/www.scientific.net/AMR.977.536.
[6] L.Y. Ding, H.L. Yu, H. Li, C. Zhou, X.G. Wu, M.H. Yu, Safety risk identification system for metro construction on the basis of construction drawings, Autom. Constr. 27 (2012) 120–137. https://doi.org/10.1016/j.autcon.2012.05.010.
[7] X. Xing, B. Zhong, H. Luo, H. Li, H. Wu, Ontology for safety risk identification in metro construction, Comput. Ind. 109 (2019) 14–30. https://doi.org/10.1016/j.compind.2019.04.001.
[8] B. Zhong, Y. Li, An Ontological and Semantic Approach for the Construction Risk Inferring and Application, J. Intell. Robot. Syst. 79 (2015) 449–463. https://doi.org/10.1007/s10846-014-0107-9.
[9] B.H.W. Guo, Y.M. Goh, Ontology for design of active fall protection systems, Autom. Constr. 82 (2017) 138–153. https://doi.org/10.1016/j.autcon.2017.02.009.
[10] A. Taroun, Towards a better modelling and assessment of construction risk: Insights from a literature review, Int. J. Proj. Manag. 32 (2014) 101–115. https://doi.org/10.1016/j.ijproman.2013.03.004.
[11] S. Laryea, Risk pricing practices in finance, insurance and construction, in: Dublin Institute of Technology, 2008. http://www.rics.org/site/scripts/download_info.aspx?downloadID=2896&fileID=3239 (accessed September 17, 2019).
[12] W. Jung, S.H. Han, Which Risk Management Is Most Crucial for Controlling Project Cost?, J. Manag. Eng. 33 (2017) 04017029. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000547.
[13] E. Mohamed, N.G. Seresht, S. Hague, A. Chehouri, S.M. AbouRizk, Domain-specific risk assessment using integrated simulation: A case study of an onshore wind project, Can. J. Civ. Eng. (2021). https://doi.org/10.1139/cjce-2021-0099.
[14] PMBOK® Guide, A Guide to the Project Management Body of Knowledge, 4th Edition, Project Management Institute, Newtown Square, Pa, 2008.
[15] J.F. Al-Bahar, K.C. Crandall, Systematic Risk Management Approach for Construction Projects, J. Constr. Eng. Manag. 116 (1990) 533–546. https://doi.org/10.1061/(ASCE)0733-9364(1990)116:3(533).
[16] R.J. Chapman, The effectiveness of working group risk identification and assessment techniques, Int. J. Proj. Manag. 16 (1998) 333–343. https://doi.org/10.1016/S0263-7863(98)00015-5.
[17] A. Rostami, Tools and Techniques in Risk Identification: A Research within SMEs in the UK Construction Industry, Univers. J. Manag. 4 (2016) 203–210. https://doi.org/10.13189/ujm.2016.040406.
[18] R.J. Chapman, The controlling influences on effective risk identification and assessment for construction design management, Int. J. Proj. Manag. (2001) 14.

[19] N.B. Siraj, A. Robinson Fayek, Risk Identification and Common Risks in Construction: Literature Review and Content Analysis, J. Constr. Eng. Manag. 145 (2019) 03119004. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001685.

[20] D. Angelopoulos, R. Brückmann, F. Jirouš, I. Konstantinavičiūtė, P. Noothout, J. Psarras, L. Tesnière, B. Breitschopf, Risks and cost of capital for onshore wind energy investments in EU countries, Energy Environ. 27 (2016) 82–104. https://doi.org/10.1177/0958305X16638573.

[21] M. Fera, R. Iannone, R. Macchiaroli, S. Miranda, M.M. Schiraldi, Project appraisal for small and medium size wind energy installation: The Italian wind energy policy effects, Energy Policy. 74 (2014) 621–631. https://doi.org/10.1016/j.enpol.2014.07.012.

[22] P. Enevoldsen, Onshore wind energy in Northern European forests: Reviewing the risks, Renew. Sustain. Energy Rev. 60 (2016) 1251–1262. https://doi.org/10.1016/j.rser.2016.02.027.

[23] Y. Rolik, Risk Management in Implementing Wind Energy Project, Procedia Eng. 178 (2017) 278–288. https://doi.org/10.1016/j.proeng.2017.01.115.

[24] G. Turner, S. Roots, M. Wiltshire, J. Trueb, S. Brown, G. Benz, M. Hegelbach, Profiling the risks in solar and wind: a case for new risk management approaches in the renewable energy sector, Swiss Reinsurance, Zurich, 2013. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&scioq=Profiling+the+risks+in+solar+and+wind&q=Profiling+the+risks+in+solar+and+wind%3A+a+case+for+new+risk+management+approaches+in+the+renewable+energy+sector&btnG= (accessed March 11, 2019).

[25] A.K. Dey, Understanding and using context, Pers. Ubiquitous Comput. 5 (2001) 4–7.

[26] F. Boukamp, E. Ergen, A proposed system architecture for context identification support on construction sites, in: 5th Int Conf Innov. Archit., Centre for Innovative and Collaborative Construction Engineering (CICE …, 2008.

[27] G. ∈st Stephan, H. ∈st Pascal, A. ∈st Andreas, Knowledge Representation and Ontologies, in: R. Studer, S. Grimm, A. Abecker (Eds.), Semantic Web Serv. Concepts Technol. Appl., Springer, Berlin, Heidelberg, 2007: pp. 51–105. https://doi.org/10.1007/3-540-70894-4_3.

[28] H.J. Levesque, Knowledge Representation and Reasoning, Annu. Rev. Comput. Sci. 1 (1986) 255–287. https://doi.org/10.1146/annurev.cs.01.060186.001351.

[29] P.T.Z. Kapauan, E. Fernandez, Knowledge Representation: A Classification with Applications in Telecommunications and the Web, in: C. Holsapple, V. Jacob, H.R. Rao, A. Chaudhury, M. Agrawal (Eds.), Bus. Model. Multidiscip. Approaches Econ. Oper. Inf. Syst. Perspect., Springer US, Boston, MA, 2002: pp. 261–291. https://doi.org/10.1007/978-1-4615-0893-9_14.

[30] T. Cao, W. Mu, J. Gou, L. Peng, A Study of Risk Relevance Reasoning Based on a Context Ontology of Railway Accidents, Risk Anal. 40 (2020) 1589–1611. https://doi.org/10.1111/risa.13506.

[31] H.M. Leung, V.M. Rao Tummala, K.B. Chuah, A knowledge-based system for identifying potential project risks, Omega. 26 (1998) 623–638. https://doi.org/10.1016/S0305-0483(98)00010-3.

[32] S. De Zoysa, Wang Yugui, Russell Alan D., Use of IT in Managing Environmental Risks in Construction Projects, in: Constr. Res. Congr. 2005, 2005: pp. 1–13. https://doi.org/10.1061/40754(183)128.

[33] R.J. Scherer, S. Reul, Retrieval of Project Knowledge from Heterogeneous AEC Documents, in: Comput. Civ. Build. Eng. 2000, American Society of Civil Engineers, Stanford, California, United States, 2000: pp. 812–819. https://doi.org/10.1061/40513(279)106.

[34] D. Kifokeris, Y. Xenidis, Analysis of Impartial Implementation in Practice of Risk Identification in Technical Projects, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part Civ. Eng. 5 (2019) 04019010. https://doi.org/10.1061/AJRUA6.0001015.

[35] X.H. Wang, D.Q. Zhang, T. Gu, H.K. Pung, Ontology based context modeling and reasoning using OWL, in: IEEE Annu. Conf. Pervasive Comput. Commun. Workshop 2004 Proc. Second, IEEE, Orlando, FL, USA, 2004: pp. 18–22. https://doi.org/10.1109/PERCOMW.2004.1276898.

[36] H.-H. Wang, F. Boukamp, T. Elghamrawy, Ontology-Based Approach to Context Representation and Reasoning for Managing Context-Sensitive Construction Information, J. Comput. Civ. Eng. 25 (2011) 331–346. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000094.

[37] S. Barati, S. Mohammadi, Enhancing Risk Management with an efficient risk identification approach, in: 2008 4th IEEE Int. Conf. Manag. Innov. Technol., 2008: pp. 1181–1186. https://doi.org/10.1109/ICMIT.2008.4654537.

[38] M.C. Garrido, M.C.A. Ruotolo, F.M.L. Ribeiro, H.A. Naked, Risk identification techniques knowledge and application in the Brazilian construction, J. Civ. Eng. Constr. Technol. 2 (2011). https://doi.org/10.5897/JCECT11.024.

[39] M. Tavakolan, A. Mohammadi, Risk management workshop application: a case study of Ahwaz Urban Railway project, Int. J. Constr. Manag. 18 (2018) 260–274. https://doi.org/10.1080/15623599.2017.1325112.

[40] C.S. Goh, H. Abdul-Rahman, Z. Abdul Samad, Applying Risk Management Workshop for a Public Construction Project: Case Study, J. Constr. Eng. Manag. 139 (2013) 572–580. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000599.

[41] S.M. AbouRizk, Risk Analysis for Construction Projects: A Practical Guide for Engineers and Project Managers, University of Alberta, NSERC Industrial Research Chair in Construction Engineering and Management, 2009.

[42] T.M. Willams, Using a risk register to integrate risk management in project definition, Int. J. Proj. Manag. 12 (1994) 17–22. https://doi.org/10.1016/0263-7863(94)90005-1.

[43] S. Somi, N. Gerami Seresht, A.R. Fayek, Developing a risk breakdown matrix for onshore wind farm projects using fuzzy case-based reasoning, J. Clean. Prod. 311 (2021) 127572. https://doi.org/10.1016/j.jclepro.2021.127572.

[44] Y. Zou, A. Kiviniemi, S.W. Jones, Retrieving similar cases for construction project risk management using Natural Language Processing techniques, Autom. Constr. 80 (2017) 66–76. https://doi.org/10.1016/j.autcon.2017.04.003.

[45] G.N.S. De Zoysa, Application and re-use of information and knowledge in managing risks of infrastructure projects, PhD Thesis, University of British Columbia, 2006.

[46] A. Aziz, S. Ahmed, F.I. Khan, An ontology-based methodology for hazard identification and causation analysis, Process Saf. Environ. Prot. 123 (2019) 87–98. https://doi.org/10.1016/j.psep.2018.12.008.

[47] J.C. Osorio-Gómez, D.F. Manotas-Duque, J.L. García-Alcaraz, Operational Risk Identification in Ground Transportation Activities: Ontology—Approach, in: G. Alor-Hernández, J.L. Sánchez-Cervantes, A. Rodríguez-González, R. Valencia-García (Eds.), Curr. Trends Semantic Web Technol. Theory Pract., Springer International Publishing, Cham, 2019: pp. 101–119. https://doi.org/10.1007/978-3-030-06149-4_5.

[48] K. Munir, M. Sheraz Anjum, The use of ontologies for effective knowledge modelling and information retrieval, Appl. Comput. Inform. 14 (2018) 116–126. https://doi.org/10.1016/j.aci.2017.07.003.

[49] N.F. Noy, D.L. McGuinness, Ontology development 101: A guide to creating your first ontology, Stanford knowledge systems laboratory technical report KSL-01-05 and …, 2001.

[50] T.E. El-Diraby, Domain Ontology for Construction Knowledge, J. Constr. Eng. Manag. 139 (2013) 768–784. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000646.

[51] T.A. El-Diraby, C. Lima, B. Feis, Domain Taxonomy for Construction Concepts: Toward a Formal Ontology for Construction Knowledge, J. Comput. Civ. Eng. 19 (2005) 394–406. https://doi.org/10.1061/(ASCE)0887-3801(2005)19:4(394).

[52] P. Pauwels, K. McGlinn, Buildings and Semantics: Data Models and Web Technologies for the Built Environment, CRC Press, 2022.

[53] J. Aguilar, M. Jerez, T. Rodríguez, CAMeOnto: Context awareness meta ontology modeling, Appl. Comput. Inform. 14 (2018) 202–213. https://doi.org/10.1016/j.aci.2017.08.001.

[54] J. Niu, R.R.A. Issa, Developing taxonomy for the domain ontology of construction contractual semantics: A case study on the AIA A201 document, Adv. Eng. Inform. 29 (2015) 472–482. https://doi.org/10.1016/j.aei.2015.03.009.

[55] T.E. El-Diraby, H. Osman, A domain ontology for construction concepts in urban infrastructure products, Autom. Constr. 20 (2011) 1120–1132. https://doi.org/10.1016/j.autcon.2011.04.014.

[56] T.E. El-Diraby, K.F. Kashif, Distributed Ontology Architecture for Knowledge Management in Highway Construction, J. Constr. Eng. Manag. 131 (2005) 591–603. https://doi.org/10.1061/(ASCE)0733-9364(2005)131:5(591).

[57] L.Y. Ding, B.T. Zhong, S. Wu, H.B. Luo, Construction risk knowledge management in BIM using ontology and semantic web technology, Saf. Sci. 87 (2016) 202–213. https://doi.org/10.1016/j.ssci.2016.04.008.

[58] S. Zhang, F. Boukamp, J. Teizer, Ontology-based semantic modeling of construction safety knowledge: Towards automated safety planning for job hazard analysis (JHA), Autom. Constr. 52 (2015) 29–41. https://doi.org/10.1016/j.autcon.2015.02.005.

[59] K. Farghaly, R.K. Soman, W. Collinge, M.H. Mosleh, P. Manu, C.M. Cheung, Construction safety ontology development and alignment with industry foundation classes (IFC), J. Inf. Technol. Constr. 27 (2022) 94–108. https://doi.org/10.36680/j.itcon.2022.005.

[60] H.P. Tserng, S.Y.L. Yin, R.J. Dzeng, B. Wou, M.D. Tsai, W.Y. Chen, A study of ontology-based risk management framework of construction projects through project life cycle, Autom. Constr. 18 (2009) 994–1008. https://doi.org/10.1016/j.autcon.2009.05.005.

[61] G. Meditskos, N. Bassiliades, D. Vrakas, I. Vlahavas, IRISPortal: a semantic portal for industrial risk cases management, in: Proc. 2nd Int. Conf. Web Intell. Min. Semant., Association for Computing Machinery, New York, NY, USA, 2012: pp. 1–8. https://doi.org/10.1145/2254129.2254164.

[62] D. Angelides, Y. Xenidis, N. Bassiliades, E. Loukogeorgaki, A. Taflanidis, D. Vrakas, S. Arnaouti, G. Meditskos, The Development of a New Framework for Managing Risks in the European Industry: The IRIS RISK PARADIGM, in: Ind. Saf. Life Cycle Eng. Technol., VCE Vienna Consulting Engineers ZT GmbH, 2012: pp. 23–56. http://www.vce.at/iris/pdf/irisbook/iris_chapter02.pdf.

[63] N.M. El-Gohary, T.E. El-Diraby, Domain Ontology for Processes in Infrastructure and Construction, J. Constr. Eng. Manag. 136 (2010) 730–744. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000178.

[64] Y. Hao, N.S. Kedir, N. Gerami Seresht, W. Pedrycz, A.R. Fayek, Consensus Building in Group Decision-Making for the Risk Assessment of Wind Farm Projects, in: 2019 IEEE Int. Conf. Fuzzy Syst. FUZZ-IEEE, 2019: pp. 1–7. https://doi.org/10.1109/FUZZ-IEEE.2019.8858797.

[65] E. Mohamed, N. Gerami Seresht, S. Hague, S. AbouRizk, Simulation-based approach for risk assessment in onshore wind farm construction projects, in: 9th Asia-Pac. Int. Symp. Adv. Reliab. Maint. Model., Vancouver, BC, Canada, 2020. https://www.researchgate.net/publication/343863437_Simulation-based_approach_for_risk_assessment_in_onshore_wind_farm_construction_projects (accessed September 12, 2020).

[66] E. Mohamed, P. Jafari, A. Chehouri, S. AbouRizk, Simulation-Based Approach for Lookahead Scheduling of Onshore Wind Projects Subject to Weather Risk, Sustainability. 13 (2021) 10060. https://doi.org/10.3390/su131810060.

[67] E. Zankoul, H. Khoury, Modeling, Animating, and Optimizing On-Shore Wind Farm Construction Operations, J. Comput. Civ. Eng. 30 (2016) 05016001. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000567.

[68] M. Bonduel, A Framework for a Linked Data-based Heritage BIM, KU Leuven, 2021. https://lirias.kuleuven.be/3416395 (accessed December 20, 2022).

[69] De Zoysa Sanjaya, Wang Yugui, Russell Alan D., Use of IT in Managing Environmental Risks in Construction Projects, in: Constr. Res. Congr. 2005, 2005: pp. 1–13. https://doi.org/10.1061/40754(183)128.

[70] S.D. Zoysa, A.D. Russell, Knowledge-based risk identification in infrastructure projects, Can. J. Civ. Eng. 30 (2003) 511–522. https://doi.org/10.1139/l03-001.

[71] S. Baker, D. Ponniah, S. Smith, Risk response techniques employed currently for major projects, Constr. Manag. Econ. 17 (1999) 205–213. https://doi.org/10.1080/014461999371709.

[72] C.S.G. Khoo, J.-C. Na, Semantic relations in information science, Annu. Rev. Inf. Sci. Technol. 40 (2006) 157–228. https://doi.org/10.1002/aris.1440400112.

[73] D.L. Rubin, N.F. Noy, M.A. Musen, Protégé: A Tool for Managing and Using Terminology in Radiology Applications, J. Digit. Imaging. 20 (2007) 34–46. https://doi.org/10.1007/s10278-007-9065-0.

[74] A. Gómez-Pérez, Towards a framework to verify knowledge sharing technology, Expert Syst. Appl. 11 (1996) 519–529. https://doi.org/10.1016/S0957-4174(96)00067-X.

[75] E. Sirin, B. Parsia, B.C. Grau, A. Kalyanpur, Y. Katz, Pellet: A practical OWL-DL reasoner, J. Web Semant. 5 (2007) 51–53. https://doi.org/10.1016/j.websem.2007.03.004.

[76] R. Danger, R. Berlanga, Generating complex ontology instances from documents, J. Algorithms. 64 (2009) 16–30. https://doi.org/10.1016/j.jalgor.2009.02.006.

[77] G. Petasis, V. Karkaletsis, G. Paliouras, A. Krithara, E. Zavitsanos, Ontology Population and Enrichment: State of the Art, in: G. Paliouras, C.D. Spyropoulos, G. Tsatsaronis (Eds.), Knowl.-Driven Multimed. Inf. Extr. Ontol. Evol. Bridg. Semantic Gap, Springer, Berlin, Heidelberg, 2011: pp. 134–166. https://doi.org/10.1007/978-3-642-20795-2_6.

[78] SPARQL 1.1 Query Language, (n.d.). https://www.w3.org/TR/sparql11-query/ (accessed August 9, 2021).

[79] DLQueryTab - Protege Wiki, (n.d.). https://protegewiki.stanford.edu/wiki/DLQueryTab (accessed August 9, 2021).

[80] E. Mohamed, P. Jafari, S. AbouRizk, Fuzzy-Based Multivariate Analysis for Input Modeling of Risk Assessment in Wind Farm Projects, Algorithms. 13 (2020) 325. https://doi.org/10.3390/a13120325.

[81] Settlers Landing Wind Park, (2017). https://www.capstoneinfrastructure.com/our-businesses/operating-facilities/SettlersLanding (accessed July 24, 2020).

[82] M. Horridge, H. Knublauch, A. Rector, R. Stevens, C. Wroe, A practical guide to building OWL ontologies using the Protégé-OWL plugin and CO-ODE tools edition 1.0, Univ. Manch. (2004).

[83] M.A. Musen, The Protégé Project: A Look Back and a Look Forward, AI Matters. 1 (2015) 4–12. https://doi.org/10.1145/2757001.2757003.

[84] Belle River Wind :: Documents, (2016). https://belleriverwind.com/project-documents/ (accessed June 16, 2020).

[85] NextEra Energy Canada - Bornish, (2013). http://www.nexteraenergycanada.com/projects/bornish.shtml (accessed June 16, 2020).

[86] Grey Highlands Clean Energy: Project Documents, (2015). https://capstoneinfrastructure.com/our-businesses/project-documents?project=Grey-Highlands-Clean-Energy (accessed June 16, 2020).

[87] Grey Highlands Zero Emission: Project Documents, (2015). https://www.capstoneinfrastructure.com/our-businesses/project-documents?project=Grey-Highlands-Clean-Energy (accessed June 16, 2020).

[88] K2 Wind: Project Documents, (2014). https://k2wind.ca/project-documents/ (accessed June 16, 2020).

[89] Port Ryerse, Boralex. (2016). https://www.boralex.com/projects/portryerse/ (accessed June 16, 2020).

Durham University
Durham Research Online

To cite this article:

Mohamed, E., Gerami Seresht, N., & AbouRizk, S. (2023). Context-driven ontology-based risk identification for onshore wind farm projects: A domain-specific approach. Advanced Engineering Informatics, 56, 101962. https://doi.org/10.1016/j.aei.2023.101962

Durham Research Online URL: https://durham-repository.worktribe.com/output/1789373

Copyright statement: Copyright © Elsevier Ltd. All rights reserved. This manuscript version is made available under the CC-BY-NC-ND 4.0 license https://creativecommons.org/licenses/by-nc-nd/4.0/