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Physics-informed Knowledge Driven Decision-Making Framework for Holistic Bridge Maintenance

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Abstract

Bridge maintenance is a highly intricate task that involves considering a wide range of factors in order to achieve optimal decisions that align with multiple objectives, criteria, and the entire lifecycle of the bridge. While physics-informed analysis, such as the finite element method (FEM), can simulate complex and closely coupled scenarios, such as bridge structural analysis, it cannot account for some loosely coupled discrete factors, which could be addressed by ontological reasoning. Therefore, this paper presents a knowledge-driven decision-making framework that combines static knowledge reasoning with dynamic FEM analysis results to support holistic bridge maintenance decisions. One significant contribution of this research is the development of a comprehensive bridge maintenance ontology that incorporates knowledge derived from bridge maintenance standards. Another key contribution is the ability to employ complex runtime rules-based reasoning to tackle intricate bridge maintenance scenarios. To enable automatic knowledge-driven reasoning, an integrated workflow is developed to orchestrate semantic modeling with numerical modeling through a Python-based Web Ontology Language application programming interface (OWL API). This integration facilitates the efficient orchestration of the framework. A case study is presented to demonstrate the potential for the developed framework in assisting with the complex holistic decisions required for bridge maintenance.

Keywords: Bridge maintenance; Knowledge engineering; Ontology; Finite element method; Holistic decision-making; Web Ontology Language; Semantic reasoning; Semantic Web**.**

Introduction

Bridges are a major component of the architecture, engineering, and construction (AEC) industry, and they are aging rapidly due to factors such as increasing traffic (Wu et al. 2021a). By the end of 2017, the total number of bridges in China that posed serious safety risks to human society was approximately 70,000 (Zhou and Zhang 2019). To restore the sub-standard bridges to optimal condition, ¥69.7 billion was invested in renovating 34,000 of China's unsafe bridges between 2016 and 2020 (Ministry of Transport of the People's Republic of China 2021). With the rapid increase in number of constructed bridges in China, optimized maintenance strategies are needed to ensure stability and safety throughout their lifecycle (Zhou and Zhang 2019; Wu et al. 2021a). Maintaining these assets is a complex process involving the identification of deterioration and defects, structure maintenance costs, safety, and environmental issues. Navigating this process requires smart, proactive, holistic methods that consider structural conditions and the bridge's entire lifecycle (Jiang et al. 2023a).

Bridge maintenance standards encapsulate extensive knowledge of safety guidelines, maintenance procedures, and environmental considerations. They are typically represented in a manner recognized by humans, which then, in some cases, are converted to a machine-readable format. Although that format is computer-readable, the domain-specific uniqueness poses a challenge for machines to achieve a nuanced semantic understanding of complex concepts (Liu and EL-Gohary 2017). Leveraging these documents in practical applications frequently demands considerable human effort to capture the diverse patterns in textual information, resulting in operational inefficiencies. To address this challenge, there is an increasing focus on leveraging the Semantic Web (SW) technologies to effectively organize and utilize domain-specific knowledge (Pauwels et al. 2017; Khudhair et al. 2021; Farghaly et al. 2023).

The SW is a group of languages or technologies (e.g., Web Ontology Language (OWL), Resource Description Framework (RDF)) that allow machines to understand the meaning or semantics of information on the World Wide Web. This facilitates the representation and integration of information from diverse knowledge domains (Pauwels et al. 2017). The development of the SW has advanced knowledge management methods from interpretation systems based on human actions to semantics-based approaches (Hou et al. 2015). As one of the core SW technologies, OWL ontology is widely used in bridge engineering. Existing ontology-based applications relating to bridge maintenance tasks can effectively integrate static information from industry manuals and norms (Ren et al. 2019; Li et al. 2021). However, there is still limited research on dynamically linking semantic reasoning to information on structural safety analysis from third-party applications. Thus, traditional SW methods utilized for bridge maintenance applications may be further enhanced.

The finite element method (FEM), which is an effective numerical method for structural analysis, is widely used in the AEC domain. Its powerful mesh processing ability can simulate complex boundary conditions and load cases to manage damage simulation, modal properties, and deterioration processes (Fan et al. 2019; Mancini et al. 2021; Smiroldo et al. 2021). Bridges are assembled from a finite number of discrete elements that are defined by structural and mechanical equations, but mathematical equations cannot express their mechanical behavior.

Thus, FEM can simulate complex behaviors of bridges. However, it is difficult to account for some loosely coupled discrete factors, such as the cause of deficiencies (or defects) and maintenance actions. Moreover, FEM has rarely been utilized for logic-based reasoning to support holistic decision-making. Since bridge maintenance must consider the results of structural physical performance, integrating FEM with knowledge-driven methods that can handle complex mathematical operations should be explored.

Therefore, by leveraging both SW and FEM, this paper presents a knowledge-driven decision-making framework that can support holistic bridge maintenance by dynamically integrating bridge lifecycle data with embedded numerical-based analysis. The fusion of different approaches can improve holistic decision-making and bridge maintenance optimization. The paper is structured as follows. Following this introduction, a literature review is provided, which outlines the most relevant findings relating to the research topic. Subsequently, the methodology, which represents the overarching framework for this research, is presented. The fourth section describes the proposed knowledge-driven decision-making framework, including ontology modeling and the Python-based reasoning mechanism. Then, a case study of an actual bridge project in China is presented to demonstrate the proposed framework. Finally, the conclusion section summarizes the key highlights of the research, while also discussing the limitations and providing recommendations for future work.

Literature Review

Review of Bridge Maintenance Standards

Bridge maintenance industry standards are widely present in various countries worldwide and are typically formulated by their respective transportation or highway management authorities. In the United States, the Federal Highway Administration (FHWA) plays a central role in developing and updating national bridge maintenance guidelines, such as the “national bridge inspection standards” (Federal Highway Administration 2022). With its extensive network of bridges, China has developed a sophisticated system of standards to ensure the structural integrity, functionality, and longevity of these critical assets. In this research, information requirements for bridge maintenance are collected based on the industry standards distributed by Ministry of Transport of the People’s Republic of China (2023), as shown in **Fig. 1**.

These standards guide the standardization of maintenance operations to ensure maintenance quality; accordingly, they include various technical requirements. For example, “the standard for technical condition evaluation of bridges (JTG/T H21-2011)” and “the specification for bridge maintenance (JTG 5120-2021)” address the current visual condition of bridges in service, maintenance operations, and technologies. Moreover, “the specification for inspection and evaluation of the load-bearing capacity of bridges (JTG/T J21-2011)” and “the specification for bridge design (JTG D60-2015)” cover the bridges’ material condition and load-bearing capacity in diverse limit states. Additionally, “the specification for strengthening design (JTG/T J22-2008)” was formulated for several types of highway bridges to restore their functions, improve their load-bearing capacity, and enhance safety. These specifications reflect the requirements of bridge maintenance. By examining their content, three key performance indicators (KPIs) relating to maintenance, along with their respective data needs, are summarized in **Table 1**. These KPIs include the current visual condition of the bridge, its material condition, and its safety performance. This knowledge serves as a guide for the subsequent development of an ontology.

Review of Ontology Applications

The term "ontology" comes from philosophy --it goes as far back as Aristotle's attempt to classify the things in the world--where it is used to deal with the nature of existence, reality, and the relationships between entities (Gruber 1995; Uschold and Gruninger 1996). In the context of Artificial Intelligence (AI), an ontology is a formal, explicit specification of a shared conceptualization (Gruber 1993; Studer et al. 1998), taking the form of a set of classes, relationships, and axiomatic constraints. "Formal" refers to the fact that it must be machine-readable. "Explicit" means that the type of concepts used and the constraints on their use are explicit. "Shared" describes consensual knowledge that is accepted by a group. In this way, ontologies provide an approach to represent knowledge in a structured and organized manner, which can be used by humans and machines, enabling efficient information retrieval, data integration, interoperability, and knowledge discovery (Saba and Mohamed 2013; Zhang et al. 2018; Xu and Cai 2020).

In bridge engineering, numerous ontologies have been developed. From 2000 onwards, some ontologies emerged with certain attributes relevant to bridge elements. For example, the ontologies developed by El-Diraby and Kashif (2005), Osman and El-Diraby (2006), and El-Diraby and Osman (2011) focus on modeling design and construction knowledge within the infrastructure domain, with some coverage of bridge elements. The in-depth focus on ontological research specifically designed for bridge engineering began in 2010 and has been continually advancing. The most prominent ontologies relating to bridge maintenance tasks are analyzed and listed in **Table 2**. The table provides information for each ontology, including their names, key concepts, uniform resource identifiers (URIs), and the language in which their latest versions are published.

These studies are divided into two groups: 1) ontology-based knowledge management and information retrieval and 2) logical inference for holistic decision-making. The first group focuses on the development of domain-specific ontologies to generate semantic relations among information sources, such as books, standards, manuals, and guides. For example, valuable data in bridge inspection reports show significant potential for improving the understanding of bridge deterioration. An analysis of these documents led to the development of BridgeOnto (Liu and El-Gohary 2016). In 2022, the BridgeOnto underwent maintenance and evaluation through various means (Liu and El-Gohary 2022). Additionally, Hu and Liu (2022) introduced a structural deterioration knowledge ontology (DT-KL-Onto) leveraging knowledge embedded in existing mathematical physics models. Moreover, Li et al. (2021) proposed the Bridge Structure and Health Monitoring (BSHM) ontology, employing an analysis of domain-specific vocabularies to enhance sensory data analysis and information sharing. By extracting terms from Chinese standards relating to bridge maintenance, Zhang et al. (2023) developed the Bridge Maintenance Domain Ontology (BMDO). BMDO covers three interconnected ontologies: the bridge structure ontology, the bridge defect ontology, and the bridge maintenance ontology. The BMDO enables rule reasoning, allowing for the automatic completion of missing relations or attribute values and the execution of consistency checks.

Studies in the second group focus on the advantage of semantics in evaluation and decision-making processes. For example, there are some ontologies for common defects on bridges. The Crack Type Ontology (CTO) and Crack Cause Ontology (CCO) introduced by Jung et al. (2020) aim to facilitate the automatic inference of concrete crack causes, reducing potential errors in human judgments. Chai and Wang (2022) developed a framework integrating computer vision and ontology to automate and standardize the assessment of concrete surface quality. Jiang et al. (2023b) presented a Bridge Corrosion Evaluation Ontology (BCEO) designed to assess the extent and severity of corrosion on railway bridges. Hamdan et al. (2021) proposed a semantic modeling approach for the automated detection and interpretation of bridge damage, consisting of two main ontologies: Damage Topology Ontology (DOT) (Hamdan et al. 2019) and Bridge Topology Ontology (BROT) (Hamdan et al. 2020). It is noteworthy that BROT was developed through the integration of BIM-related bridge information, allowing the definition of bridge constructions, including aggregated zones and components, along with their topological relations. Furthermore, Ren et al. (2019) developed the Bridge Maintenance ontology (BrMontology) to manage the heterogeneous and discrete knowledge in the bridge maintenance domain and enable smarter decision-making. By using semantic rules, relatively powerful reasoning capabilities are achieved, including automation of the bridge evaluation process, sorting and providing information about bridge maintenance, assisting in selecting material suppliers, and assisting in arranging big events. It facilitates a smarter decision-making process for bridge management by informing engineers of choices with different considerations rather than a single objective-targeted delivery. In another contribution, Wu et al. (2021b) proposed a Concrete Bridge Rehabilitation Project Management Ontology (CBRPMO) to address the need to enhance information integration and automate information retrieval in bridge rehabilitation projects. A standout feature of the CBRPMO is its effectiveness in managing information in ongoing projects. It supports various management functions based on project information, encompassing the evaluation of project progress, removal of constraints, and assessment of participants' performance.

In both groups, ontology modeling is achieved by adhering to a series of standards set by the World Wide Web Consortium (W3C) (2024). The aim is to ensure interoperability between ontologies in different systems, enhance maintainability, and provide consistency and connectivity for applications. These include standards to identify resources (i.e., URI), bind a meaning to every information atom (i.e., OWL), perform logic-based reasoning (i.e., semantic web rule language (SWRL) and shapes and constraints language (SHACL)), and to query information (i.e., SPARQL Protocol and RDF Query Language (SPARQL) and Semantic Query-Enhanced Web Rule Language (SQWRL)).

Based on the review of the aforementioned studies, two critical issues are identified:

(1) **Ontologies for holistic bridge maintenance.** Most existing ontologies are designed to achieve specific goals, e.g., bridge deterioration prediction, structural health monitoring, and bridge damage evaluation. Bridge maintenance is a complex task that requires the consideration of a wide range of factors, with the analysis of structural safety performance being a crucial aspect. However, the content in current ontologies lacks coverage of

structural analysis. Therefore, there is a need for a comprehensive bridge maintenance ontology that includes classes and properties not only relating to bridge elements and damage types but also associated with structural physical performance.

(2) **Ontology reuse**. Although an increasing number of ontologies have been developed, many are still difficult for researchers to find, access, and understand due to issues such as the absence of valid URIs. Ren et al. (2019) and Farghaly et al. (2023) emphasized the significance of researchers reviewing existing ontologies and integrating them into their work. Therefore, a simple and effective method for creating accessible, understandable, and reusable ontology on the web should be investigated.

Methodology

This section describes the general methodology of this research. The overarching framework that we propose for broader adoption is shown in **Fig. 2**. The framework consists of two steps: (1) lifecycle data integration for finite element model generation and (2) physics-informed logical-based reasoning for holistic maintenance.

(1) Lifecycle data integration for finite element model generation. Using the ANSYS parametric design language (APDL), a script was developed to generate and optimize a finite element model that integrates data from different lifecycle stages. Based on the data collected from the design and construction phases, the geometric model of bridge sections was built and exported in a standard ACIS Text (SAT) format, which is used to store 3D model geometry. The exported file was then imported into ANSYS to generate an initial finite element model using APDL.

During the operation and maintenance phase, bridge owners regularly conduct bridge inspections. The collected data from these inspections is then stored in the bridge management system (BMS). The characteristics of the initial model are optimized using these stored data. The optimization of dynamic characteristics was conducted using the response surface method (RSM), with the natural frequency of the structure as the objective and material parameters as design variables. RSM primarily uncovers analytically complicated or unknown relationships between several inputs and the desired output through empirical models (Chakraborty and Sen 2014; Kim et al. 2017). The established response surface equation and the objective function are shown in Equations 1 and 2.

The Monte Carlo Simulation (MCS), which is a probability analysis method involving random sampling to observe the results (Kartal et al. 2011), was performed to find the optimal solution. Thus, the value of the objective function (F'_{obj}) was calculated by randomly adjusting the values of the design variables within its range, with the value of the design variables corresponding to the smallest F'_{obj} being the optimal solution.

$$y_k = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} b_{ii} x_i^2 \qquad (1)$$

$$F'_{obj} = \sqrt{\sum_{k=1}^{m} c_k \cdot (Y_k - y_k)^2} \qquad (2)$$

where, Y_k is the measured response; y_k is the target response; *x* is the design parameter; b_0 is the constant term coefficient; b_i is the linear term coefficient; b_{ij} is the cross-term coefficient; b_{ii} is the quadratic term coefficient; c_k is the coefficient for the importance of each term; *n* is the number of design parameters; and *m* is the number of the response.

For the optimization of the static characteristics, an iterative optimization approach was employed to modify the initial model's necessary internal force responses, which were considered as the design variables. The established objective function is shown in Equation 3. The value of the objective function ($F_{obj}^{''}$), was calculated after each adjustment of the design variables. When its value converges, the optimization results can be obtained. Finally, the optimized model was used to analyze the safety performance,

$$F_{obj}'' = \sqrt{\sum_{i=1}^{n}(T_i - T_i')^2} \qquad (3)$$

where *n* is the number of optimized internal force responses; $T_i^{'}$ is the response of the initial model; and T_i is the response of the inspection data source.

(2) Physics-informed logic-based reasoning for holistic bridge maintenance. A comprehensive ontology that integrates domain knowledge relating to bridge maintenance was developed. Ontology Development 101 was selected to build the ontology since it provides guidelines for implementing an ontology that is accessible to inexperienced developers (Noy and McGuinness 2001). Protégé was employed as the ontology management system to model, edit, and work with the ontology. It has several plugins, such as SWRL and pellet reasoner, which were used in this research. Pellet reasoner was used to check the structure of the proposed ontology during its development to ensure correctness and consistency between its terms.

SWRL provides a mechanism for expressing complex relationships and logical constraints that surpasses what can be expressed using OWL ontologies alone. The knowledge required to evaluate the structural condition is expressed in the form of SWRL rules. Specifically, the evaluation methods are as follows:

- **Visual condition evaluation**. The current visual condition can be assessed by indicators such as technical condition level. In accordance with the standard JTG/T H21-2011, the level of the bridge's visual condition (D_j) is determined based on the value of the bridge's overall technical condition (D_r). D_r (Equation 4) is calculated using the combination of stratified condition assessments and five levels of an independent control index,

$$D_r = BDCI \times W_D + SPCI \times W_{SP} + SBCI \times W_{SB} \qquad (4)$$

where $BDCI$, $SPCI$, and $SBCI$ denote the technical conditions of the bridge deck system, superstructure, and substructure, respectively. W_D, W_{SP}, and W_{SB} represent the coefficients for the importance of the bridge deck system, superstructure, and substructure in a bridge. These coefficients are assigned values of 0.4, 0.4, and 0.2, respectively.

- **Material condition evaluation**. In bridge maintenance operations, the concrete strength of the structure is an important benchmark for evaluating the material condition. In accordance with the standard JTG/T J21-2011, the level of the bridge's material condition (S_j) is determined based on the value of the uniformity coefficient of the calculated strength of concrete (K_{bt}). According to bridge inspection data, Equation 5 is used to calculate K_{bt},

$$K_{bt} = R_{it}/R_d \qquad (5)$$

where R_{it} is the calculated value of the actual strength of concrete and R_d is the grade of concrete design strength.

- **Safety performance evaluation**. The safety performance of a bridge is calculated based on indicators of the components' load-bearing capacity and the indicator of strengthening design. In line with the standard JTG/T J21-2011, the level of the bridge's safety performance (Z_j) is determined for serviceability limit states and ultimate limit states. Based on the standard JTG D60-2015, in serviceability limit states, the characteristic value of permanent action is combined with the quasi-permanent value of variable action applied to bridges. In contrast, in ultimate limit states, the most unfavorable combination of the permanent action effect and uncertainties effect is applied to bridges. The load-bearing capacity of a bridge's structure or component is then calculated using Equation 6,

$$\gamma_0 S \leq R \qquad (6)$$

where R is the resistance value of members' load-bearing capacity, influenced by material properties and the geometric dimensions of the structure; γ_0 is the coefficient for the structure's importance in a road network; and S is the effect function of actions combination, which varies with the combination of loads acting on the structure. If $z_i = \gamma_0 S_i / R_i$ $(i = 1,2,3)$, then Z_j can be inferred.

Due to the influence of many factors, the structural performance of in-service bridges is likely to degrade to the point at which they no longer meet minimum requirements. Therefore, strengthening measures are necessary and selected as appropriate to a particular problem. This research uses the bonded steel plate method as an example (**Fig. 3**). In line with the standard JTG/T J22-2008, the corresponding calculations are provided in Equations 7-9,

$$f_{cd} b x_1 = f_{sd} A_s + f_{sp} h_{sp} b - f'_{sd} A'_s \qquad (7)$$

If $2a'_s \leq x_1$,

$$\gamma_0 M_d \leq f_{cd} b x_1 \left(h_0 - \frac{x_1}{2}\right) + f'_{sd} A'_s (h_0 - a'_s) - f_{sp} h_{sp} b a_s \qquad (8)$$

If $x_1 < 2a'_s$,

$$\gamma_0 M_d \leq f_{sd} A_s (h_0 - a'_s) + f_{sp} h_{sp} b (h_0 - a'_s) \qquad (9)$$

where *b* and *h* are the width and height of the section, respectively; f_{cd} is the design value of concrete compressive strength; f_{sd} ands $f_{sd}^{'}$ are the design values of the tensile strength of the steel bar in the tension zone and compression zone, respectively; a_s and $a_s^{'}$ are the distances from the steel bar to the section in the tension zone and compression zone, respectively; A_s and $A_s^{'}$ are the cross-sectional area of the steel bar in the tension zone and compression zone, respectively; x_1 is the height of the compression zone; f_{sp} is the strength of the reinforced steel plate; h_{sP} is the thickness of the reinforced steel plate; and M_d is the value of the bending moment (members' load-bearing capacity) after strengthening.

All the evaluation results above are included in Equation 10 to obtain the multi-objective decision-making in the form of a summation of weighted reasoning results,

$$F_{obj} = \omega_1 D_j + \omega_2 S_j + \omega_3 Z_j \qquad (10)$$

where ω_i is the weighting coefficient, which indicates the significance of each component from 0 to 1, with the sum being 1. The exact value of ω_i can be determined by the bridge engineer according to certain conditions. For instance, if bridge structural safety is taken as the governing consideration, then $\omega_1 = 0.2$, $\omega_2 = 0.3$, and $\omega_3 = 0.5$. Based on the resulting value of F_{obj}, maintenance decisions (daily maintenance, preventive maintenance, repair maintenance, special maintenance, and emergency maintenance) can be inferred.

Moreover, a Python-based OWL API was established to achieve automatic inference processes. The datasets collected from Step 1 and the ontology model were loaded by combining Openpyxl, a library that provides a way to read, write, and modify Excel spreadsheets in Python, with Owlready2, a library that can load OWL files as Python objects, modify them, save them, and perform reasoning. Subsequently, all datasets were added to the BMO to permit reasoning. Finally, bridge engineers can access maintenance information that satisfies certain criteria by using SPARQL queries provided by RDFLib, which is a Python library allowing users to work and access OWL files. Bridge engineers can query information about structural visual and material conditions, structural safety performance in different states, and maintenance decisions based on multiple objectives. Different strengthening measures are provided in case a bridge's safety performance does not meet requirements.

A Knowledge-driven Decision-making Framework

Bridge Maintenance Ontology (BMO) Development

This section discusses the development and implementation of the ontology. As discussed above, Ontology Development 101 (Noy and McGuinness 2001) was selected to build the proposed knowledge base, and Protégé was employed as the ontology management system. **Fig. 4** illustrates the iterative design process of the proposed ontology.

The domain of the proposed BMO is the bridge maintenance field. It is designed to improve the maintenance knowledge management of the bridge lifecycle and provide more valuable information than that of older methods, thereby enabling bridge engineers to make holistic decisions. Reusing the existing ontology's critical elements can provide a knowledge base that is compatible with other ontologies. Hence, several ontologies were reviewed to evaluate reusability and extensibility, such as the bridge maintenance ontology (BrMontology) proposed by Ren et al. (2019) and the linked open vocabularies (LOV) database (2023). However, it was concluded that although these ontologies provide a solid initial foundation, they use strictly static data and do not adequately cover bridge maintenance knowledge. Consequently, in this research, the BMO takes those ontologies as a base for development and extends them. By leveraging the FEM results, the BMO can utilize not only static knowledge but also dynamic information.

As discussed in the literature review, terms relating to bridge maintenance were collected by analyzing specifications and manuals distributed by China's Ministry of Transport. The collected terms were then divided into distinct categories (classes) and properties such as object properties, data properties, and annotation properties. A top-down method (Uschold and Gruninger 1996) was used to define the class hierarchy. Keywords, standards, and criteria analysis in these specifications were developed as classes or subclasses. Relationships were defined as object or data properties. The "facets", that is, the values of properties, were also added. Finally, individuals, also known as instances, were added to the class hierarchy.

A unified modeling language (UML) diagram of the initial version of the BMO is shown in **Fig. 5**. At the highest level of abstraction, twelve core classes were defined. The "Bridge" and "Organization" classes were used to describe generic information relating to bridges, such as name, address, total length, and maximum span length. The classes "BridgeStructure", "BridgeComponent" and "BridgeMember" were defined in detail to represent the structural and non-structural elements of a bridge. Moreover, the “Material”, “MaterialSupplier”, “Hazard” and “PotentialReason” classes are reused from the BrMontology ontology (Ren et al. 2019). They were linked together to describe knowledge relating to structural visual and material conditions. In terms of structural safety performance, the “LimitStates” class and its subclasses, such as “ServiceabilityLimitStates” and “UltimateLimitStates,” were defined. The “MaintenanceSolution” and “StrengtheningMeasure” classes were created to provide maintenance and strengthening measures.

Properties create connections in the above classes to form RDF triples. An RDF triple consists of a subject, predicate, and object. For example, the object properties “buildBy” and “managedBy” connect individuals belonging to the class “Bridge” to individuals belonging to the class “Organization”, resulting in the corresponding RDF triples: “Bridge, buildBy, Organization” and “Bridge, managedBy, Organization”. The object properties “hasStructure”, “hasComponent” and “hasMember” are the connection and subordinate relations among the structural entities; they have corresponding inverse properties such as “isStructureOf”, “isComponentOf” and “isMemberOf”, and quantifier restrictions, such as “someValues”, which make the ontology more complete. The object properties “hasHazard”, “hasMaterialType”, “hasCapacity”, “hasMaintenanceSolution” and “hasStrengtheningMeasure” belong to a design pattern to implement n-ary (n binary) relations (W3C Working Group 2006). Therefore, individuals belonging to the class “Bridge” can be depicted based on different properties.

Furthermore, data properties, which connect individuals to multiple datatypes, describe the characteristics of various individuals quantitatively and qualitatively. The BMO utilizes string, int, float, and Boolean datatypes. For example, the name and identification (ID) of bridges are assigned as string, while the characteristics of individuals belonging to the class "Material" are assigned as float. Whether the bridge needs strengthening is determined by returning a Boolean type. Individuals in the BMO and their facets are also added. For example, according to the standard JTG 5120-2021, individuals belonging to the class "MaintenanceSolution" were added, including "DailyMaintenance", "PreventiveMaintenance", "RepairMaintenance", "SpecialMaintenance", and "EmergencyMaintenance".

Creation of Semantic Rules

The BMO was already capable of running built-in reasoners and searching for static information via SPARQL queries. However, it could not handle the complex evaluation and structural safety analysis problems discussed in the methodology section. To further improve its ability, five sets of semantic rules were created to support deductive reasoning using the formal logic of SWRL in Protégé editor. A total of 55 SWRL rules include visual condition, material condition, safety performance, maintenance decisions, and strengthening measures. The workflow of the inference process is shown in **Fig. 6**. Of note, some of these rules are conditional (highlighted in yellow) and rely on the dynamic FEM results.

Table 3 displays several SWRL examples. An SWRL rule consists of two main parts, the antecedent (body) and the consequent (head), observed at the left and right sides, respectively, and connected by the symbol "→". Both the antecedent and consequent consist of zero or more atoms, which are connected by '^'. An "atom" refers to the smallest element, serving as the fundamental building block for constructing more complex logical expressions. Satisfaction of the atoms in the antecedent renders the atoms in the consequent true. The SWRL provides the class atom, individual property atom, and data-valued property atom. **Table 4** lists several of the atoms used in this research. Atoms in SWRL rules can take the form C(x), P(x,y), sameAs(x,y), or differentFrom(x,y), where C is an OWL description, P is an OWL property, and x and y are either variables, OWL individuals or data values. Moreover, there are built-in atoms (e.g., swrlb:add, swrlb:lessThan) in SWRL. They support many complex predicates that can translate mathematical equations into semantic rules. Thus, both the mathematical operations and reasoning syntaxes are implemented by exploiting SWRL.

Integrating FEM with Logic-based Reasoning

SWRL has limitations due to the underlying RDF/OWL syntax. Some reasoning processes involve extremely complex mathematical operations that require the support of advanced computer-aided tools. For instance, for various actions, the value of the combination is given by the function (S_i), which can be obtained using FEM. Moreover, specific axioms relating to individuals needed to be defined in some reasoning processes, e.g., the material types of the bridge's various components. Therefore, a Python-based OWL API was set up to support automatic inference processes.

Fig. 7 shows the overall workflow of the process. Firstly, the required data were stored in an Excel (.xlsx) file in a structured way. Bridge inspection and structural property data can be obtained directly from the bridge's project report. For FEM data, APDL is applied to extract

ANSYS post-processing results and store them in the Excel file. Secondly, Openpyxl and Owlready2 libraries were combined to load the datasets in the Excel and ontology files, respectively. By using these packages, the data in the Excel sheets were converted into RDF triples that map onto the relevant classes, attributes, and relationships in the proposed ontology. This involved identifying the appropriate ontology classes and attributes corresponding to data and associating them with RDF triples. For example, the datasets include a bridge named "Changshan Bridge." This name, "Changshan Bridge", corresponds to an individual of the class "Bridge" in the proposed ontology. By applying the proposed algorithm, the following RDF triple was created: "ChangshanBridge, is_a, Bridge".

Then, deductive reasoning was performed based on the as-built SWRL rules by running the inference engine. New knowledge was derived through the reasoning process, which enriches the original ontology; as such, an ontology can be continually updated, reasoned, and searched for the timely delivery of both static and dynamic information. To give an example of the enrichment, the class "Bridge" acquired a new individual "Changshan Bridge," the safety performance of the individual was good, and daily maintenance was the maintenance solution. Finally, using SPARQL queries provided by the RDFLib library, the new ontology was queried to retrieve maintenance information that satisfies certain criteria. The seamless connection of the above steps facilitated the logical reasoning process that was supported by FEM results.

Accessing the Proposed BMO on the Web

The process is designed to integrate various tools to create accessible, understandable, and reusable BMO on the web (**Fig. 8**). First, an OWL file of BMO with metadata and definitions for terms was used as input. Wizard for documenting ontologies (WIDOCO), proposed by Daniel Garijo (Garijo 2017; Garijo and Poveda-Villalón 2020), generates a set of HTML files that were linked through a nexus file, a file for facilitating documentation publication through content negotiation and serializations of the ontology to enable different formats of the documentation and ontology. All these files were input into GitHub repositories to build and deploy a web page. When publishing an ontology on the web, it is recommended to consider its long-term sustainability, specifically the consequences if it becomes widely adopted. Finally, the "w3id.org" website (W3C Permanent Identifier Community Group 2023), run by the W3C permanent identifier community group, was used to provide a secure, permanent URL re-direction service for web applications. After integrating Protégé, WIDOCO, w3id.org website, and GitHub, the generated permanent URL of BMO was produced (https://w3id.org/BMO), which is easy to access, understand, and reuse by end-users.

Case Study

In this section, a practical application of the physics-informed knowledge-driven framework is demonstrated through the Changshan Bridge, a cable-stayed bridge with a length of 540m (140m+260m+140m) located in Dalian, Liaoning Province (Jiang et al. 2020). The layout of the main bridge is shown in **Fig. 9**. Its main beam is fixed to its pier and pylon. Considering the geological and topographical conditions at the site, the Changshan Bridge is located toward the northern end of the North Yellow Sea Fault Depression, introducing the possibility of uncertain events, such as magnitude six or higher earthquakes. For structural safety analysis, its loading conditions encompass not only typical load types like dead, temperature, and vehicle loads but also include seismic action. **Table 5** lists the load types and loading methods in FEM software for the Changshan Bridge. Additional concerns involve the coastal environment and susceptibility to common defects like cracks and spalling. The service scenario of the Changshan Bridge involves aspects relating to its visual and material condition, as well as safety performance; therefore, inferring holistic maintenance decisions requires logic-based reasoning supported by a physics-informed analysis.

Generation Finite Element Model of the Changshan Bridge by integrating lifecycle data

As shown in **Fig. 10**, the initial finite element model of the Changshan Bridge was developed in ANSYS. Material parameters for the model were set according to the traffic and environmental conditions at the bridge site. The geometric configuration of the model was directly generated based on the data from the construction drawings. This model is designed as a spine model, concentrating the mass and stiffness of the deck system on the main girder nodes. Cables and main beam nodes are connected by steel arms. Then, the model is optimized based on data from “The Annual Report on the Professional Maintenance Project of the Changshan Bridge in 2019” (hereinafter referred to as the maintenance report), issued by the Liaoning Provincial Transportation Planning and Design Institute. A four-factor Box-Behnken design method is used to establish samples for optimization of the dynamic characteristics. The change rate of the material parameter value is the correction parameter, including the elastic modulus and density of the beam, as well as the elastic modulus and density of the pylon (four factors). The natural frequencies of the first five orders of its structure are the correction targets. The values of the coefficients in Equation 1 were calculated according to the results of samples in the Box-Behnken design. The relationship between random numbers in the Monte Carlo algorithm and the value of F'_{obj} in Equation 2 is listed in **Table 6**. When the total random number reaches 10^6, F'_{obj} converges, yielding dynamic optimization results.

For the optimization of the static characteristics, the cable forces of the initial model were modified. The cable force of the initial model was assumed to be $T_i^{'}$, the force from the maintenance report was T_i, and the difference between the two was k_i (Equation 11). According to the difference k_i, the pretension of the initial model was adjusted. The value of $F_{obj}^{''}$ in Equation 3 was calculated after each adjustment of the pretension,

$$k_i = {}^{(T_i' - T_i)}\!\Big/_{T_i} \times 100\% \qquad (11)$$

where i is the number of cables (i= 1, 2, 3, ..., n), and n=34 for the Changshan Bridge.

The change of $F_{obj}^{''}$, with the number of iterations, is listed in **Table 7**. After ten iterations, the value of $F_{obj}^{''}$ converged closely, and the optimized cable force value was consistent with the measured data, indicating that the characteristics of the optimized model were consistent with those of the actual bridge. A more detailed description of this process is provided in our previous paper (Jiang et al. 2020).

The structural safety analysis in two limit states was performed using the optimized model, with loadings specified in **Table 5**. **Fig. 11** shows the internal force cloud diagram of the bridge under the serviceability limit states. The entire section is compressed, and the maximum axial compressive stress is 8.69 MPa. Under the ultimate limit states, the beam is fixed to its pier and pylon; therefore, the fixed position, especially the bottom of the pylon, is significantly damaged by seismic vibration (Jiang et al. 2020). The bending moment of the pylon is extracted with the maximum bending moment, 11.8×10^4 kNm (**Fig. 12**).

Physics-informed Inferences and Maintenance Decision-making

The reasoning process and results are shown in **Fig. 13**. The datasets, including bridge inspection data, the FEM analysis data, and the bridge property data, as well as the BMO ontology, were loaded via the Python-based OWL API in the Python environment. Based on the created Python code, these data were automatically mapped to the ontology's relevant classes, attributes, and relationships. The "Changshan Bridge" was defined as an individual belonging to the class "Bridge" in the ontology. Its data were added to corresponding data and object property assertions. In addition, a material condition inspection of the bridge was carried out on various parts of the structure, e.g., the pylon and girder. Due to the different material types of the different members, the corresponding individuals and their object property assertions were also added in addition to data property assertions. Running the reasoning engine to execute as-built SWRL rules, the level of visual condition, material condition, and structural safety performance of the "Changshan Bridge" were inferred automatically, with D_j= 2, S_j=1, and Z_j=1, respectively. The material condition and the safety performance were both positive. There were areas of slight damage on the bridge but no influence on functions. Following that, ω_i(i=1,2,3) are 0.2, 0.3, and 0.5, respectively, which denoted bridge structural safety as the overriding consideration. The reasoning result of F_{obj} is 1.2, and it is determined that the maintenance decision was daily maintenance.

In addition, the decision of strengthening measures was also evaluated. As shown in **Fig. 14**, under the ultimate limit states, $z_3 > 1.0$, i.e., the resistance value (8.06×10^4 kNm) is less than the effect value of the combined actions (11.8×10^4 kNm), indicating that the bridge needs strengthening measures. The tensile side of the pylon should be reinforced with bonded steel plates. Engineers can determine the thickness of the bridge's steel plates, which is set to 4.5–50 mm as the default. The as-built SWRL rules can be applied to obtain the load-bearing capacity of the strengthened bridge. For example, when the Q390 plate with a thickness of 30 mm is selected, and the new reasoning result of $z'_3 < 1.0$, the solution meets the requirements. For a more in-depth comparison, the outputs of the inferred bending moment values in different solutions are illustrated in **Fig. 15**. Options for strengthening the bridge can be compared and selected from the nine groups that meet the criteria. Bridge maintenance personnel can also choose appropriate solutions from these options based on local steel plate types and prices.

Finally, rather than manually searching through information scattered across documents and systems, bridge engineers can use SPARQL queries to find maintenance information that satisfies their specified criteria. For example, they can query maintenance solutions for bridges with overall condition as the primary consideration (**Fig. 16**). This allows engineers to better understand the bridge, considering factors such as structural condition and maintenance solutions.

Conclusion

This paper presents a knowledge-driven decision-making framework that synergistically merges static knowledge reasoning with dynamic insights gained from FEM analysis to support holistic bridge maintenance decisions. By following standard procedures, the research developed a bridge maintenance ontology to integrate all the essential terminology and required data for bridge maintenance. One of the research's main contributions is to enable complex, runtime rule-based reasoning to address complex bridge maintenance scenarios. To achieve this, an integrated workflow to orchestrate semantic modeling with numerical modeling through a Python-based OWL API was developed, which enabled automatic, physics-informed, knowledge-driven reasoning.

Like any research, the research acknowledges its limitations, including the fact that the current validation is only relevant to one bridge scenario and that FEM necessitates substantial computational resources, particularly for larger structures, where an enormous number of elements are required, maintenance decision-making is computationally expensive and time-consuming. Therefore, enhancing and refining the framework will require further validation of different bridge scenarios. With the exponential growth in the popularity of AI, there is a growing interest among researchers in utilizing machine learning (ML) techniques to evaluate the structural safety performance of bridges. In forthcoming studies, an ML-based surrogate model will be employed to forecast the safety performance of bridges, thereby significantly reducing the time and expenses associated with the FEM analysis process.

The proposed knowledge base is now accessible on the internet, granting users the capability to access, comprehend, and seamlessly integrate it with other management and maintenance systems in the future. This framework introduces an innovative approach that effectively integrates various decision-making techniques. By incorporating real-time numerical analysis, the static knowledge base can be enhanced, resulting in more comprehensive and semantically meaningful rule sets that are better equipped to handle intricate decision scenarios.

Data Availability Statement

All data, models, or codes that support the findings of this research are available from the corresponding author upon reasonable request.

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Table 1. KPIs for bridge maintenance

Category	**Key Performance Indicators**	**Data needs**
Visual condition	Indicator of technical condition level	Bridge inspection data
Material condition	Indicator of concrete strength level	Non-destructive inspection data
Safety performance	Indicator of load-bearing capacity Indicator of strengthening design	Material property data Structural property data FEM analysis results

Table 2. Ontologies in bridge maintenance

Name	**Acronym**	**Concepts**								**URI**	**Language**
		T	E	M	D	C	S	A	P		
Bridge Deterioration Ontology (Liu and El-Gohary 2016; Liu and El-Gohary 2022)	BridgeOnto	X	XX	O	XX	XX	O	XX	O	/	OWL; SWRL
Damage Topology Ontology (Hamdan et al. 2019)	DOT	O	O	O	X	X	O	O	O	https://www.w3id.org/dot	OWL; SPARQL; SHACL
Bridge Maintenance Ontology (Ren et al. 2019)	BrMontology	O	X	O	X	X	O	X	O	/	OWL; SQWRL; SWRL
Bridge Topology Ontology (Hamdan et al. 2020)	BROT	X	X	X	O	O	O	O	O	https://www.w3id.org/brot	OWL; SWRL
Crack Type Ontology (Jung et al. 2020)	CTO	O	O	O	XX	O	O	O	O	/	OWL
Crack Cause Ontology (Jung et al. 2020)	CCO	O	O	O	O	XX	O	O	O	/	OWL
Bridge Structure and Health Monitoring Ontology (Li et al. 2021)	BSHM	X	X	O	O	O	XX	O	O	https://github.com/chongqing-jiaotong-university-ai-lab/BridgeHealthMonitoring	OWL; SPARQL; SWRL
Concrete Bridge Rehabilitation Project Management Ontology (Wu et al. 2021b)	CBRPMO	O	X	O	O	O	O	XX	XX	/	OWL; SQWRL: SPARQL; SWRL
Concrete Surface Defect Ontology (Chai and Wang 2022)	/	O	X	O	XX	XX	O	X	X	/	OWL; SWRL

Structural Deterioration Knowledge Ontology (Hu and Liu 2022)	DT-KL-Onto	O	O	O	XX	XX	O	O	O	/	OWL
Bridge Corrosion Evaluation Ontology (Jiang et al. 2023b)	BCEO	X	X	X	X	X	O	O	X	https://w3id.org/BCEO (Invalid link)	OWL; SWRL
Bridge Maintenance Domain Ontology (Zhang et al. 2023)	BMDO	X	XX	O	XX	O	O	XX	O	http://www.semanticweb.org/kert/ontologies/2022/6/BMDO (Invalid link)	OWL; SWRL

Note: T = Bridge Type; E = Bridge Element; M = Material Properties; D = Deficiency (or Defects); C = Deficiency (or Defects) Cause; S = Sensors Configuration; A = Maintenance Action; P = Project Participation. O= not covered; X = rarely covered; and XX = moderately covered.

Table 3. Examples of SWRL rules

Rules for calculating the value of visual condition, $D_r = BDCI \times W_D + SPCI \times W_{SP} + SBCI \times W_{SB}$
VisualCondition(?B)^BDCI(?B,?Bbd)^SPCI(?B,?Bsp)^SBCI(?B,?Bsb)^Wd(?B,?Bwd)^Wsp(?B,?Bwsp)^Wsb(?B,?Bwsb)^swrlb:multiply(?k1,?Bbd, ?Bwd)^swrlb:multiply(?k2,?Bsp, ?Bwsp)^swrlb:multiply(?k3,?Bsb, ?Bwsb)^swrlb:add(?Bdr,?k1,?k2,?k3)->Dr(?B,?Bdr)
Rules for calculating the uniformity coefficient of inferred strength of concrete, $K_{bt} = R_{it}/R_d$
BridgeMember(?B)^Rit(?B,?Brit)^Rd(?B,?BRd)^swrlb:divide(?Bkbt,?Brit,?BRd)->Kbt(?B,?Bkbt)
Under ultimate limit states, rules for calculating safety performance coefficient. $z_i = \gamma_0 S_i/R_i$ $(i = 1,2,3)$
Bridge(?B)^r0(?B,?Br0)^S3(?B,?BS3)^swrlb:multiply(?Bk,?Br0,?BS3)^R3(?B,?BR3)^swrlb:divide(?Bz,?Bk,?BR3)->z3(?B,?Bz)
Rules for calculating the value of objective function, $F_{obj} = \omega_1 D_j + \omega_2 S_j + \omega_3 Z_j$
Bridge(?B)^Dj(?B,?BDj)^Sj(?B,?BSj)^Zj(?B,?BZj)^w1(?B,?Bw1)^w2(?B,?Bw2)^w3(?B,?Bw3)^swrlb:multiply(?k1,?BDj,?Bw1)^swrlb:multiply(?k2,?BSj,?Bw2)^swrlb:multiply(?k3,?BZj,?Bw3)^swrlb:add(?sum,?k1,?k2,?k3)->Fobj(?B,?sum)
If 1.5≤ F_{obj} **<2.5, rules for reasoning about maintenance decisions.**
Bridge(?B)^Fobj(?B,?Bj)^swrlb:greaterThanOrEqual(?Bj,1.5)^swrlb:lessThan(?Bj,2.5)->hasMaintenanceSolution(?B,PreventiveMaintenance)^maintenancePlaning(?B,"Protective measures need to be taken to delay the degradation of structural performance and prolong the service life of the bridge.")
If z_3 **≤1, rules for reasoning about the result of strengthening demands.**
Bridge(?B)^z3(?B,?Bz3)^swrlb:lessThanOrEqual(?Bz3,1)->needStrengthening(?B,false)
Rules for calculating the height of compression zone, $f_{cd} b x_1 = f_{sd} A_s + f_{sp} h_{sp} b - f'_{sd} A'_s$
StrengtheningMeasure(?B)^hsp(?B,?Bhsp)^b(?B,?Bb)^swrlb:multiply(?BAsp,?Bhsp,?Bb)^fsp(?B,?Bfsp)^swrlb:multiply(?BFsp,?BAsp,?Bfsp)^Fcd(?B,?BFcd)^Fsd1(?B,?BFsd1)^Fsd2(?B,?BFsd2)^F_sd1(?B,?BF-sd1)^F_sd2(?B,?BF-sd2)^swrlb:add(?k1,?BFsd1,?BFsd2,?BFsp) ^swrlb:add (?k2,?BF-sd1,?BF-sd2) ^swrlb:subtract(?k3,?k1,?k2)^swrlb:divide(?k4,?k3,?BFcd)->x1(?B,?k4)

Table 4. Examples of atoms used in this research

Atom type	Atom	Corresponding OWL element
Class atom	Bridge (?B)	Bridge (class)
	BridgeMember (?Bm)	BridgeMember (class)
Data valued property atom	Dj (?B,?Bdj)	Dj (data-type property)
	Sj (?B,?BSj)	Sj (data-type property)
	Zj (?B,?BZj)	Zj (data-type property)
	Fobj(?B,?Bj)	Fobj (data-type property)
Object property atom	hasMaterialType(?B,?BM)	hasMaterialType (object property)
	hasStrengtheningMaterial(?B,?BSM)	hasStrengtheningMaterial (object property)
Built-in atom	swrlb:add(?Bdr,?k1,?k2,?k3)	
	swrlb:greaterThanOrEqual(?Bdr,95)	
	swrlb:lessThan(?Bdr,60)	

Table 5. The load types and loading methods

Name	Load types	Description	Loading methods	APDL script
Dead load	Permanent action	The weight of concrete beam, main pylon and stay cables.	Add to the concrete material properties	MP,DENS,1, 2678
		10cm asphalt concrete bridge deck pavement, 7cm cement concrete bridge deck pavement, anti-collision guardrail, marking signs, lamp posts, cable pipelines and water pipes.	Loaded as MASS21 mass element	ET,4,MASS21 R,35,4.898E3,4.898E3,4.898E3
Temperature load	Variable action	The annual average temperature is 9.7°C.	Loaded in the form of element load	BF,all,TEMP,9.7
Vehicle load	Variable action	The vehicle load level is class I, and the design speed is 60 km/h.	Loaded in the form of lane load	SFBEAM,all,1,PRES,10500 F,52,FY,-360000
Seismic action	Seismic action	There is a probability of an earthquake of magnitude-6 or higher.	The EI-Centro wave (Seismic action E2) conducts the co-excitation along the axial and vertical axes.	*dim,ACCEXY,TABLE,1000,4 *tread,ACCEXY,E2-EI,txt,, *dim,ACCEX,array,1000 *dim,ACCEY,array,1000

Table 6. The relationship between random numbers and the objective function

Number of random numbers	10^1	10^2	10^3	10^4	10^5	10^6
F'_{obj}	0.0815	0.0776	0.0296	0.0159	0.0037	0.0033

Table 7. The change of the objective function with the number of iterations

Number of iterations	1	2	3	4	5	6	7	8	9	10	11	12	13
F''_{obj}	6.2	2.2	1.5	1.4	1.3	1.2	1.2	1.1	1.0	1.0	0.9	0.9	0.9