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Interactive self-contained compliant structure design supported by multi-objective knowledge inference

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ABSTRACT

Modern structural design must balance design criteria with increasing objectives like cost minimization, carbon reduction, and stakeholder interests. However, this multi-domain knowledge exists in unstructured forms, such as text, formulas, and tables, and converting it into machine-readable structured knowledge within a unified knowledge framework remains challenging. This paper proposes an ontology-based knowledge modeling and mapping approach to transform unstructured knowledge from design specifications, cost, and carbon emissions into structured knowledge. This approach enables self-containing compliance with structural design standards and supports multi-objective trade-offs. Furthermore, ontology models are transformed into backend services to facilitate interactive design. The developed system has been rigorously tested and validated through case studies. This method promotes the standardization, intelligence, and sustainability of the structural engineering and construction industries, significantly enhancing the overall efficiency and collaboration within the sector.

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Structure; multi-objective design; ontology; knowledge inference; knowledge mapping

Introduction

In contemporary engineering practice, there is a growing emphasis on meeting social requirements for sustainable development and comprehensive performance (Castañón, García-Granda, Guerrero, Lorenzo, & Angulo, 2015; Chen, Okudan, & Riley, 2010; García-Segura & Yepes, 2016; García-Segura, Penadés-Plà, & Yepes, 2018). Structure design has shifted from focusing solely on single indices (Afzal, Liu, Cheng, & Gan, 2020; Eleftheriadis, Mumovic, Greening, & Chronis, 2015; Yucesan & Viana, 2023) to prioritizing the attainment of a balance across multiple objectives. These objectives encompass structural safety, reliability, economy, environmental friendliness, and more. This requires innovative approaches to meet the growing attention to technological advancements, the increasing complexity of designs, diverse stakeholder concerns, the evolving technological landscape, and the need to avoid impractical or overly heavy structures. This transition has propelled structural design towards a multi-objective direction. Even though the need for multi-objectives in structural design is increasing, it is still essential to follow and satisfy the design codes and specifications(C&S) used in traditional structural design. The calibration of these C&S is an ongoing process that is important for maintaining the security of national and global infrastructure systems. As a result, novel approaches are needed to meet the challenges of modern structural design in achieving multiple design objectives while ensuring compliance with C&S standards.

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With the development of computer technology, multi-objective design has achieved significant results (Afzal et al., 2020). Several prominent approaches have emerged, each contributing to different aspects of optimization. Firstly, parametric design approaches, such as Building Information Modeling (BIM) – based methods that utilize parametric modeling, provide a more flexible framework for changes in design parameters (Eleftheriadis et al., 2015; Yucesan & Viana, 2023). For example, (Oti & Tizani, 2015) applied the principles of feature-based modeling to extract information from the BIM model, focusing on sustainable analysis during the initial phase of structural design.

In addition to parametric methods, machine learning (ML)-based methods provide a new dimension to the multi-objective design with strongly correlated objectives and automatically achieving trade-offs between multiple objectives (Dede, Kripka, Toğan, Yepes, & Rao, 2018; Jiang, Ding, Song, Geng, & Wang, 2022; Liu et al., 2021; Tyflopoulos, Tollnes, Steinert, & Olsen, 2018). For example, (Zhao, Liao, Xue, & Lu, 2022) proposed an intelligent layout design method based on deep neural networks for reinforced concrete shear-wall structures, which considered multiple design objectives of vertical displacement of typical floor slabs, concrete usage, and steel usage; (Huang, Zhang, Ann, & Ma, 2020) used a multi-objective design approach to automate the mixing ratio design of steel fiber reinforced concrete.

Recent research has made significant strides in advancing multi-objective structural design. However, design C&S, as indispensable references for structural design, are challenging to integrate into current multi-objective methodologies. This difficulty arises because C&S are often represented in multi-source formats, such as textual descriptions, formulas, and material properties. These are not readily convertible into quantifiable and structured data compatible with parametric modeling and ML-based frameworks. As a result, design outcomes frequently lack feasibility, compliance, and efficiency, leading to increased costs associated with manual validation and modifications. Furthermore, this limitation can compromise overall project quality and delay implementation timelines.

Ontology, as an advanced semantic technology capable of clearly representing and processing knowledge structures, offers unique advantages in addressing challenges. By defining concepts, property, and their relationships, ontology provides a unified semantic framework for design. Also, the ontology introduces a knowledge reasoning function based on a unified semantic framework that allows for connecting, analyzing, and reasoning about implicit knowledge through semantic logic rules and an inference engine. This facilitates automated calculations and decision-making in the multi-objective design process. While ontology-based structural design methods have made significant progress in multi-objective structure design, they primarily focus on considering multiple objectives. For example, some researchers have applied ontology to the design of various structures, including frame structures (Zhang, Li, Zhao, & Ren, 2018), cylindrical structures (Hou, Li, & Rezgui, 2015) and pile structures (Meng, Cui, Li, & Liu, 2022; Zhang, Cui, Li, Zhang, & Liu, 2021). However, the full potential of ontology has not yet been fully realized, particularly in seamlessly integrating design C&S into the structural design process, where there remains significant room for improvement.

Therefore, this paper aims to extend the functionality of ontology in structural design based on knowledge mapping and reasoning to address the above needs. The main contributions are as follows. First, an ontology-based knowledge mapping method is proposed that integrates weakly correlated multi-domain knowledge (e.g. C&S, domain expert knowledge, sustainability, and cost) and maps different types of knowledge (e.g. material parameters, design calculation methods, design requirements) from C&S into an ontology model. This methodology is self-contained and compliant while addressing multi-objective design. It can independently generate designs that fully adhere to industry standards without relying on external tools or manual intervention. This significantly enhances both the efficiency and accuracy of the design process. In addition, the ontology model has been integrated into a backend service to facilitate interactive design, enabling engineers to participate in the design process through queries, thereby enhancing usability in real-world applications.

This paper is structured as follows: section 2 reviews multi-objective structural design. Section 3 demonstrates the Framework design and development method. Section 4 shows a case study of system validation. Finally, Section 5 gives the key conclusions.

Review of multi-objective structural design

With the development of computer technology, various multi-objective design methods have emerged. For example, integrating BIM technology with multiple dimensions (nD BIM) has become a key focus in architectural and structural engineering research. The nD BIM represents dimensions beyond the traditional three-dimensional model, including time, cost, sustainability, and beyond. This extended functionality holds multi-objective considerations promise for enhancing the capabilities of structural design processes (Oti, Tizani, Abanda, Jaly-Zada, & Tah, 2016). For example, (Zanni, Sharpe, Lammers, Arnold, & Pickard, 2019) investigated how BIM policies, technologies, and methods can facilitate more accurate predictions of whole-life costs at the design decision-making stage, thereby saving time and effort in achieving quality assurance more effectively. (Shin, Kim, & Choi, 2016) integrated management environment of BIM property information as a new approach for generating a reliable sustainability simulation model in the BIM-based design process. The practical implementation of nD BIM faces challenges that have hindered its effective and comprehensive results. Integrating multiple dimensions, such as time, cost, and sustainability, into BIM has proven complex, with issues related to data standardization and interoperability between software applications and stakeholders. Technological limitations in existing BIM tools and a lack of standardized collaboration practices contribute to the industry's slow adoption. Resistance to change within traditional construction practices, cost considerations, and limited regulatory support impede the widespread use of nD BIM. Additionally, the need for a skilled workforce and industry-wide collaboration poses further barriers (Zhang et al., 2018).

ML-based approaches introduce a new dimension by leveraging advanced algorithms to complex design spaces. These methods are particularly advantageous for solving context-specific, tightly relational multi-objective designs (Jiang et al., 2022; Kripka, Yepes, & Milani, 2019). For example, (Liu et al., 2021) proposed a multi-objective design method considering cost, efficiency, and accuracy for automatically placing reinforcement bars in RC structures. (Zavala, Nebro, Luna, & Coello Coello, 2014) used a heuristic algorithm to solve the structural multi-objective design problem between cost and safety. (Chiu & Lin, 2014) employed ML methods to achieve a multi-objective structure design with minimum cost, failure probability, concrete cover spalling probability, maximum plausibility, and minimum maintenance events.

Ontology, the most critical technology in knowledge systems, has attracted attention for its strength in integrating weakly connected multidisciplinary knowledge and its ability to enable information sharing between humans and computers (Choi, Song, & Han, 2006; Da Silva, Revoredo, Baião, & Euzenat, 2020; Ivanova, 2019). Ontology achieves unified knowledge representation and semantic interrelation by defining standardized knowledge models such as the resource description framework (RDF) and web ontology language (OWL). Consequently, ontology is influential in integrating multi-domain knowledge and multi-source data. For example, in the architecture, engineering, and construction (AEC) domain, ontology in combination with other digital technologies such as BIM (Niknam & Karshenas, 2017), geographic information systems (Fonseca, Egenhofer, Davis, & Borges, 2000), and the Internet of things (Sharma et al., 2021) are utilized to address various aspects including cost estimation, health monitoring, holistic decision – making (Farghaly, Soman, & Zhou, 2023). In addition, ontology-based solutions have enhanced data exchange between multiple platforms. For example, some research focused on integrating BIM authoring platforms such as Navisworks and Revit (Lee, Kim, & Yu, 2014) while other studies developed bespoke platforms to address interoperability challenges (Hu & Liu, 2020; Ren et al., 2019).

Ontology enables the integration of multi-domain knowledge through a unified knowledge representation. Furthermore, with the mining and use of semantic rules, the potential of ontology for structural design has been initially discovered. Semantic rules can express design specifications, regulations, conditions, and constraints. Meanwhile, logical reasoning combines explicit and implicit knowledge, allowing the ontology to store and retrieve information and dynamically infer new knowledge. This capability provides the foundation for handling complex mathematical representations and calculations in structural design. As a result, ontology demonstrates strong adaptability in addressing complex design objectives and supporting integrated decision-making. For example, (Zhang et al., 2018) presented a holistic approach based on ontology to facilitate a more thoughtful decision-making process for the early design stage by informing designers of the environmental impact, cost, and safety considerations. (Hou et al., 2015) investigated how ontology and semantic web rules can be used in a knowledge-based system to represent information about structural design and sustainability and to facilitate decision-making in the design process. (Zhang et al., 2021) developed the bridge deck decision system ontology based on the ontology method and semantic web rule language (SWRL). It can automatically provide financial, safety, and heat flux information for designers to evaluate and optimize the design scheme in the early design stage of a bridge.

The literature review demonstrates significant progress in the field of multi-objective structural design. The BIM-based multi-objective design offers a more intuitive way to present design schemes, and its parametric modeling enables faster adjustments to design elements, supporting various design variables. Furthermore, the standardized data format ensures consistency in design information, making the optimization process easier to trace and verify. ML-based multi-objective design methods can learn complex nonlinear relationships from large datasets, significantly reducing computation time while effectively balancing conflicts between closely related objectives. Ontology-based structural design methods leverage the high flexibility of ontology in integrating multi-domain knowledge, demonstrating significant advantages in addressing and balancing multi-objective considerations.

Overall, current research has advanced structural design toward multi-objective development. However, there is a lack of consideration of C&S, which results in design outcomes that require additional manual compliance checks by experts, resulting in inefficiencies and error-prone. This paper aims to expand the application of ontology in multi-objective structural design, leveraging its powerful semantic modeling and reasoning capabilities, focusing on addressing the challenge of integrating codes and standards (C&S) into the design process.

Framework design and development

Framework design

Figure 1 shows the methodology proposed in this paper, which consists of two main parts: ontology development and interactive web service development.

Firstly, the ontology model, named 'OntoDesign' integrates unstructured knowledge of C&S with multiple objectives such as cost, carbon emissions, and safety into an ontology-based structured knowledge. The workflow for OntoDesign can be summarized as follows: A skilled knowledge engineer integrates various domains of expertise relevant to structure design, including design C&S, material costs, sustainability considerations, and optimization techniques. These diverse knowledge inputs are systematically transformed into a unified knowledge model and semantic and query rules.

Then, an interactive web service is developed to facilitate user interaction with the design process, allowing users to input design requirements and preferences directly into the knowledge model. This enables a seamless exchange between users and the knowledge system.

The development details of ontology and interactive web service as shown in 3.2 and 3.3, respectively.

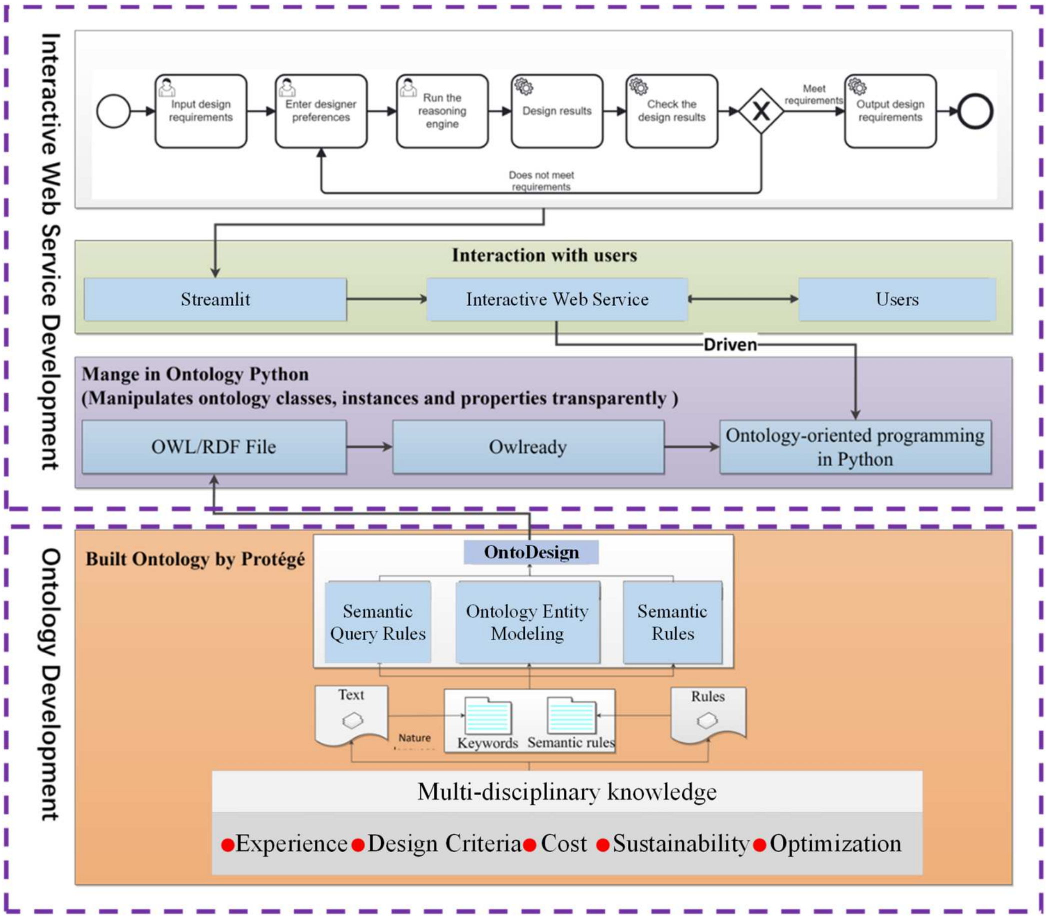


Figure 1. Workflow of Interactive self-contained compliant structure design method.

Ontology-based multi-objective knowledge molding and mapping method

Knowledge mapping

Ontology formally represents knowledge about concepts and their relationships in a specific domain. It can model the relationships between concepts in the domain into a structured form more suitable for application in computer systems. The ontology entity model includes classes, individuals, objects, and data properties. Figure 2 illustrates the basic concepts and their relationships using domain knowledge from the bridge engineering field. A class represents a category or concept in a particular domain. For instance, in bridge design, 'Bridge,' 'Pier,' and ' Beam' are all examples of classes. An individual is a specific object or entity that belongs to a class. For example, C30 concrete is a particular individual of the class 'Material.' Object properties describe relationships between classes or individuals. It connects different concepts or entities within the ontology. For example, a beam is a structure component, and its material includes C30 concrete. Data properties describe specific features or attributes of a class or individual, typically using simple types like numbers and strings. For example, parameters such as the beam's length and width, the concrete's density, and the cost are included.

Sources of multi-objective structural design knowledge include descriptions, methods, and material parameters related to design C&S, cost, and sustainability. This information exists as unstructured knowledge, such as text (e.g. names of components and materials such as 'beam'

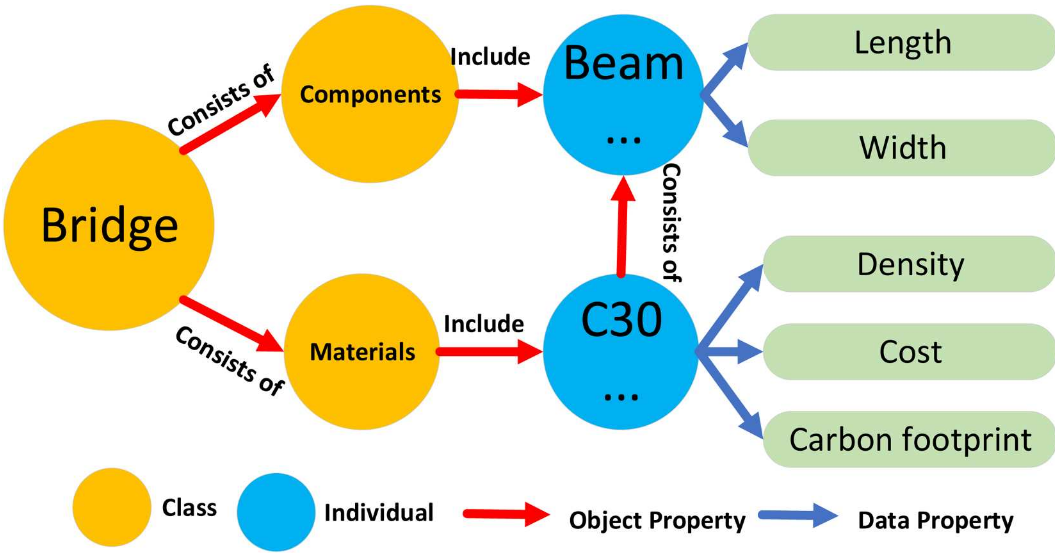


Figure 2. The example of basic concepts of ontology and their relationships.

and 'concrete'), parameters (e.g. mechanical properties of the material such as 30 MPa), and conditions (e.g. maximum displacement not to exceed L/800 of the span length). Figure 3 illustrates the ontology-based knowledge mapping method, which transforms unstructured knowledge into structured semantic content. Precisely, knowledge in the form of text and parameters is mapped to ontology entities. Text is expressed in the form of classes and individuals, and knowledge in the form of parameters is described as data properties. Classes and individuals are associated through logic, and then individual and data properties are associated with object properties.

In addition, the conditions and constraints from C&S or legal clauses can be converted into semantic rules such as SWRL and SQWRL. SWRL is a logic-based semantic rule language that can establish connections between knowledge and help the system automatically infer hidden information. For example, structural design methods are expressed by mathematical formulas, which can be represented by SWRL rules, as shown in Table 1. This SWRL rule consists of several components working together to calculate the cross-sectional area of a beam. The rule starts by

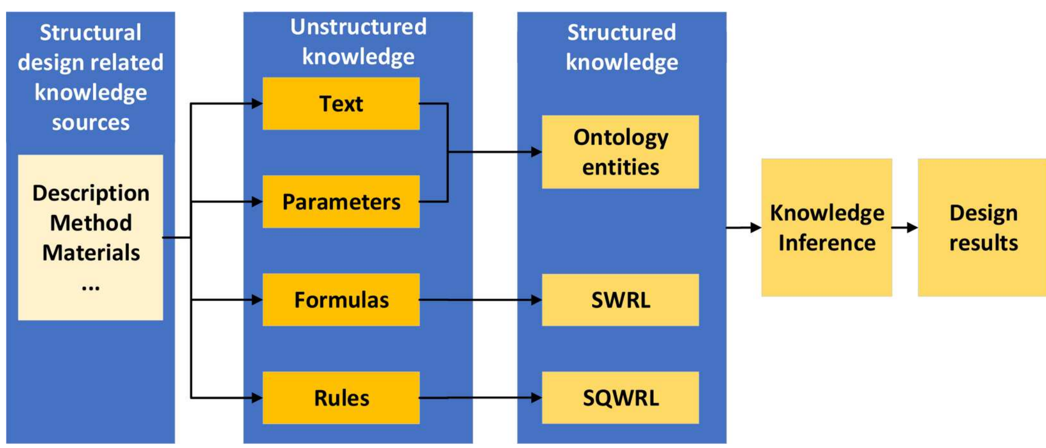


Figure 3. Ontology-based knowledge mapping method.

Table 1. SWRL and SQWRL rules examples.

SWRL. rules example
Calculate the cross-sectional area: $Ac = b \cdot h$
Beams(?B)^b(?B,?Bb) ^h(?B,?Bh) ^swrlb:multiply(?B,?Bb,?Bh) – >Ac(?B,?BAc)
SQWRL example
Beam(?B)^Length(?B,?BL)^MaxLength(?BL,?y) ^ fc(?B,?Bfc) ^ swrlb:lessThan(?Bfc, y/600)
->sqwrl:select(?B,?Bwfk,?Bfc,?BTotalCO2,?BTotalCost,?RC)

identifying the beam instance (?B) and retrieving its width (?Bb) and height (?Bh) from the ontology. Using the built-in 'swrlb: multiply' function, it computes the product of these two values to determine the cross-sectional area (?BAc). Finally, the calculated area is assigned to the beam's 'Ac' property, enriching the ontology with this derived knowledge. Each rule component ensures the calculation process is logical, consistent, and seamlessly integrated into the ontology framework.

Semantic Query Web Rule Language (SQWRL) is a query language, similar to database queries, that can extract and filter information from an ontology. For example, SQWRL can filter results based on the design requirement 'the maximum deflection of the main beam in a beam bridge should not exceed 1/600 of the calculated span length' and provide feedback to the user, as shown in Table 1, 'MaxLength(?BL,?y)' represents the maximum span length, and 'fc(?B,?Bfc)' denotes the maximum deflection. The condition swrlb:lessThan(?Bfc, y/600) ensures that the maximum deflection is less than 1/600 of the span length. The rule '->sqwrl:select(?B,?Bwfk,?Bfc,?BTotalCO2,?BTotalCost,?RC)' outputs all relevant parameters for solutions that meet this requirement.

The proposed method demonstrates generalizability in transforming various codes, safety requirements, and environmental guidelines into an ontology. Despite the differences in the content of these documents, the underlying knowledge is consistently represented in the form of text, parameters, formulas, or rules. This consistency allows for a systematic and uniform conversion of diverse regulatory information into the ontology framework, enhancing the system's adaptability across different contexts.

Ontology development

After the knowledge mapping, the ontology modeling will follow the ontology development 101 method (Noy, 2001). As shown in Figure 2, the process includes eight steps and begins with defining the scope of knowledge for building the ontology. Next, the potential for ontology reuse is considered. After that, the critical terms within the specified knowledge scope are enumerated. Subsequently, classes, properties, instances, and semantic rules are created.

This paper introduces NLP techniques into the ontology modeling process to improve the efficiency and comprehensiveness of vocabulary extraction from C&S. As shown in Figure 4. The term frequency-inverse document frequency (TF-IDF) approach is applied to extract key terms and word frequency statistics in relevant documents, which is instrumental in enabling knowledge engineers to discern the criticality of vocabulary during the modeling phase. By analyzing term frequencies within specific documents and evaluating their rarity across the entire corpus, TF-IDF identifies key terms and assigns significance based on their contextual importance. This nuanced understanding empowers knowledge engineers to make informed decisions, thereby elevating the quality of the ontology.

TF-IDF enhances the modeling process by quantifying and prioritizing relevant terms, ensuring a more accurate and meaningful representation of semantic relationships within the ontology. Term frequency, tf(t,d), as shown in equation (1), is the relative frequency of term t within document d. As shown in equation (2), the inverse document frequency measures how much information the word provides, i.e. if it is common or rare across all documents. It is the logarithmically scaled inverse fraction of the documents that contain the word (obtained by dividing the total number of documents

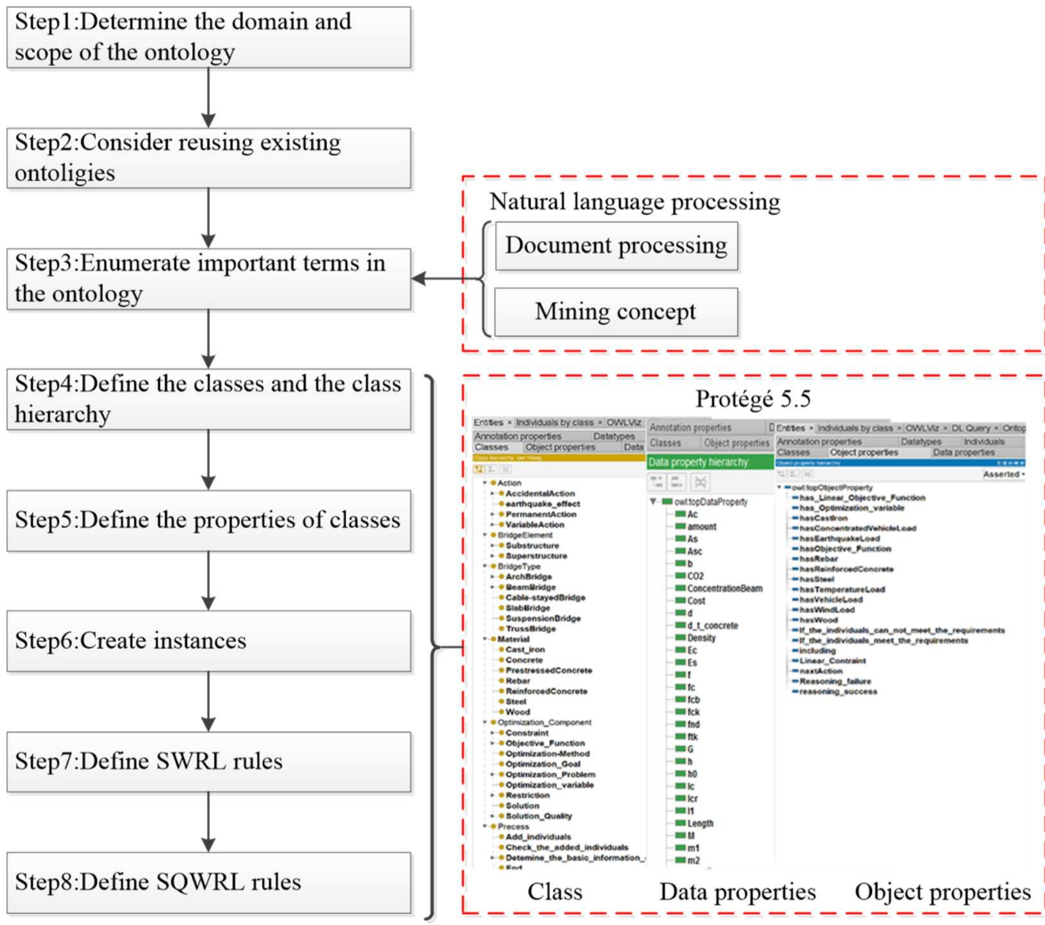


Figure 4. Ontology development process.

by the number of documents containing the term, and then taking the logarithm of that quotient):

$$\mathrm{tf}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \tag{1}$$

$$\mathrm{idf}(t, d) = \log \frac{N}{|\{d \in D : t \in d\}|} \tag{2}$$

Where N is the total number of documents in the corpus $N = |D|$. $|\{d \in D : t \in d\}|$ is the number of documents where the term t appears (i.e. $\mathrm{tf}(t, d) \neq 0$). If the term is not in the corpus, this will lead to a division-by-zero. It is therefore common to adjust the denominator to $1 + |\{d \in D : t \in d\}|$.

The ontology-based multi-objective structural design knowledge model established using the aforementioned method is illustrated in Figure 5. Note that the ontology model is not fully expanded for clarity in presenting the content. In the figure, 'squarebeam2-8' represents a cross-section whose data attributes include the dimensions of the cross-section. It is also related to the individual of materials (C40–R235), the individual of load (Vehicle1) using Object properties ('hasRebar', 'hasConcentratedLoad Vehicle1', 'hasReinforcedConcrete'). At the same time, the C40–R235 Individual has cost-related data properties (cost), implied carbon energy data properties (CO2), and mechanical properties such as modulus of elasticity (Ec) in the specification.

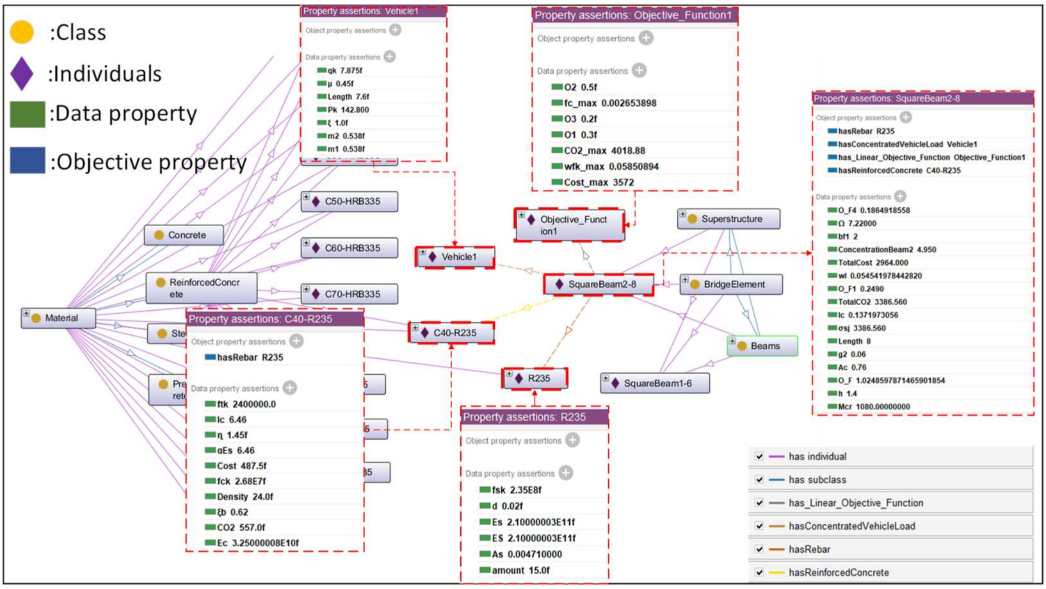


Figure 5. Examples of entities shown in the knowledge graph.

Interactive web services development method

The development of ontology facilitates the realization of multi-objective structure design through knowledge-based reasoning. Nevertheless, operational challenges persist for structure designers attempting to utilize the ontology for comprehensive design. This segment of the study focused on crafting an intuitive and user-friendly interface to enhance the accessibility and usability of the developed system.

The interactive web service development method is shown in Figure 6. The service comprises a front-end user interface and a backend ontology interaction engine. The interactive interface is developed using (Streamlit, 2024), collects user information, and displays analysis results. Streamlit is an open-source Python framework designed to efficiently create interactive data applications for machine learning and data science teams. The backend employs Owlready (Lamy, 2017) as the ontology interaction tool. Owlready (Lamy, 2017) is a Python package designed for ontology-oriented programming, capable of loading OWL 2. The ontology model described in Section 3.2 is saved as an OWL file and read into the Python environment using Owlready.

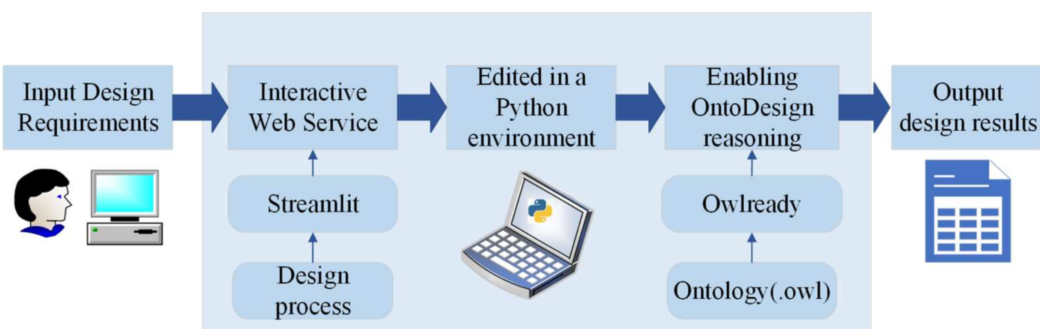


Figure 6. The development of interactive web services.

The flow of using this interactive web service is as follows: The user enters the design requirements (e.g. span length, deck width, load level.) on the front-end page and then inputs them through the front-end developed by Streamlit, which then writes to the ontology model and triggers ontology reasoning via Owlready. For example, data attributes such as span and beam width are edited for all beam section Individuals in the ontology model. Given that beam section Individuals are associated with different material Individuals, running the reasoner triggers the parallel computation of various design scenarios (with other sections and materials), resulting in multiple design results that meet the design criteria. The final design results are exported in.xls format and returned to the user.

Case study

The specific development process and effects of the method proposed in this paper will be illustrated through the case of simply supported beam design and further demonstrate the extensibility of the method using the case of continuous beam design.

Those case studies take the Design Code of Highway Reinforced Concrete and Prestressed Concrete Bridges and Culverts (Code for Design of Highway Reinforced Concrete and Prestressed Concrete Bridges and Culverts (JTG 3362–2018), 2018) as an example and incorporate it into the ontology-based multi-objective structure design model.

Ontology development of bridge design

In this case study, the multi-domain knowledge consists of the following five fields: bridge design standard, material carbon emission database, material cost database, optimization knowledge, and human design experience. The Entities in the ontology model developed for this case study include 93 Classes, 16 object properties, 83 Data properties, and 58 Individuals. The following sections will provide a detailed explanation of the knowledge and rules incorporated into this case study.

Incorporate bridge design experience and C&S into ontology models

Bridge design mainly relies on two aspects of knowledge: the human experience. In particular, the selection of bridge type needs to consider the purpose of construction, application, landscape requirements, and other social factors, which need to be judged by the experience of bridge design engineers. For example, if the bridge span is less than 8 m and is only used for traffic without aesthetic requirements, choose a simply supported bridge. The SWRL rules are shown in Table 2, '->' on the left side represents the design conditions, and the right side represents the inference results. In details, 'BeUsedFor(?B, Transportation)' checks whether the beam is used for transportation; 'IsThereAnAestheticRequirement(? B, No)' checks whether there are no special aesthetic requirements; 'swrlb:lessThan(?y,8)' checks whether its maximum length is less than 8 m. '->HasBridgeType(?B,SimplySupportedBridge)' means if all these conditions are true, the system concludes that the beam type is a 'Simply Supported Bridge.'

On the other hand, the Chinese bridge design specification (Code for Design of Highway Reinforced Concrete and Prestressed Concrete Bridges and Culverts (JTG 3362-2018), 2018) is

Table 2. SWRL rules for selecting bridge types.

If the bridge span is less than 8 m and is only used for traffic without aesthetic requirements, then choose a simply supported bridge.
Beam(?B)^Length(?B,?BL)^MaxLength(?BL,?y)^BeUsedFor(?B,Transportation)^ IsThereAnAestheticRequirement(? B,No)^swrlb:lessThan(?y,8) ->HasBridgeType(?B,SimplySupportedBridge)

Table 3. The concrete specification parameter value.

Specification parameter	C25	C30	C35	C40	C45	C50	C55	C60	C70
f_{ck}(MPa)	16.7	20.1	23.4	26.8	29.6	32.4	35.5	38.5	44.5
f_{tk}(MPa)	1.78	2.01	2.20	2.40	2.51	2.65	2.74	2.85	3.00
E_c(MPa) $\times 10^4$	2.80	3.00	3.15	3.25	3.35	3.45	3.55	3.60	3.70
Density(T/m^3)	2.38	2.385	2.39	2.40	2.41	2.42	2.44	2.47	2.55

used as an example to integrate it into the ontology model in this case study. The related descriptions, material parameters, coefficient specifications, and calculation rules of the bridges in the specifications were extracted. The details are as follows:

(1) Material characteristic specification. The choice of materials is a critical issue in bridge design and is directly related to the bridge's safety performance. Reinforced concrete bridges, as an example, concrete and steel bars are the two primary materials used in the construction process. The material properties of concrete and steel bars are specified in the specifications, as shown in Tables 3 and 4. They are relevant specification parameters of 9 different strength concrete and four types of steel bars used in reinforced concrete and prestressed concrete components.

Where, f_{sk} is axial compressive strength; f_{sd} is axial tensile strength; E_c represents modulus of elasticity;

Where, f_{sk} is tensile strength standard value; f_{sd} is the tensile strength design value; f_{sd}' is compressive strength design value; E_s is the modulus of elasticity;

(1) Coefficient specification. In the bridge design and calculation process, besides the self-weight of the bridge caused by various materials, other variable loads, such as varying effects caused by automobile loads, also need to be considered. The choice of some coefficients will depend on the bridge's location, the type of bridge, and the choice of bridge material, such as the level of vehicle load, the standard value of vehicle load, and the long-term growth coefficient of deflection.
(2) Calculation methods in the design specifications. The bridge design specifications require crack limits and deflections of flexural members. For example, the calculation method of deflection under short-term and long-term loads in the code is used to illustrate the calculation process and method of converting it to the SWRL rule, as shown in Table 5.
(3) Design requirements: This case study transforms the design requirements into semantic query rules. As shown in Table 6. Q1 is to select a design plan that meets the requirements of 'the cracking width of reinforced concrete members in typical environments does not exceed 0.2mm' and 'the maximum beam deflection must be verified to be less than 1/600 span'. Q2 outputs the calculation results of the optimization function.

Incorporate multi-objective knowledge into ontology models

In addition to integrating experience and standards into the ontology, the case also integrates sustainability, cost, and optimization knowledge into the ontology model as described below:

Table 4. Rebar specification parameter value.

Specification parameter	R235	HRB400	HRB300	KL400
f_{sk}(MPa)[a]	235	400	335	400
f_{sd}(MPa)[b]	195	330	280	330
f_{sd}'(MPa)[c]	195	330	280	330
E_s(MPa)[d] $\times 10^5$	2.1	2.0	2.0	2.0

Table 5. SWRL rules for deflection calculation.

Deflection of the bridge under short-term load: Beams(?B)^M(?B,?BM)^length-cal(?B,?Bla)^G(?B,?BG)^swrlb:multiply(?fnd1,5,?BM,?Bla,?Bla,1000) ^swrlb:multiply(?fnd2,48,?BG)^swrlb:divide(?Bfnd,?fnd1,?fnd2)->fnd(?B,?Bfnd)
Deflection under long-term load: Beams(?B)^fnd(?B,?Bfnd)^hasReinforcedConcrete(?B,?RC) ^ReinforcedConcrete(?RC)^η(?RC,?RCη) ^swrlb:multiply(?Bfc,?Bfnd,?RCη)->fc(?B,?Bfc)

Table 6. SQWRL rules.

Q1 Select all design solutions that meet the safety calculation Beams(?B) ^σcc(?B,?Bσcc)^σsj(?B,?Bσsj)^fc(?B,?Bfc)^TotalCO2(?B,?BTotalCO2) ^ TotalCost(?B,?BTotalCost)^ wfk(?B,?Bwfk) ^hasReinforcedConcrete(?B,?RC)^ReinforcedConcrete(?RC)^fck(?RC,?RCfck) ^hasRebar(?RC,?R)^Rebar(?R) ^swrlb:lessThan(?Bwfk,0.2)^swrlb:lessThan(?Bfc,l/600) >sqwrl:select(?B,?Bσcc,?Bσsj,?Bfc,?BTotalCO2,?BTotalCost,?RC,?R)
Q2 Select the optimized function calculation result Beams(?B)^O_F(?B,?BO_F)^hasReinforcedConcrete(?B,?RC)^ReinforcedConcrete(?RC) ->sqwrl:select(?B,?BO_F,?RC)

(1) Concrete Sustainability Performance Database.

Carbon emissions are an unavoidable factor in structural design. Concrete is the primary carbon-containing material in most buildings and infrastructures. Focusing on the carbon emissions implicit in using concrete is one of the fastest measures to reduce emissions. This study selected nine types of Chinese commercial concrete with different strengths as examples, and their implied carbon energy per unit volume is shown in Table 7. The energy consumed by these nine types of concrete is calculated by the Inventory of Carbon & Energy database (Embodied Carbon Assessment – Circular Ecology, 2023), including the energy consumed directly and all the energy consumed indirectly, the total energy consumed during the product's processing, manufacturing, and transportation.

(2) Material Cost

Materials costs are highly valued in the cost estimation process. Since concrete prices vary in different regions, this calculation is based on the average prices of eight major concrete suppliers in Beijing, China. October 10, 2020. The prices of the nine types of concrete selected in this article

Table 7. Nine kinds of Chinese commercial concrete embodied carbon energy calculation table.

	Material consumption (kg/m^3)									
Concrete type	Water-Cement ratio	Sand rate (%)	Water	Cement	Mineral powder	Fly ash	Sand	Stone	Admixture	Embodied Carbon energy (kg/m^3)
C25	0.51	44	180	224	44	83	844	1075	1.61	432
C30	0.52	41	185	285	0	70	770	1090	1.71	427
C35	0.50	34	180	310	0	50	630	1223	1.87	448
C40	0.42	34	185	380	0	60	604	1171	2.28	557
C45	0.4	40	195	440	0	49	685	1030	6.6	613
C50	0.33	38	180	490	0	54	638	1043	7.4	657
C55	0.522	37	173	333	0	0	702	1195	0	515
C60	0.34	37	170	500	0	0	685	1165	FDN	661
C70	0.39	35	195	500	0	0	312	1139	FDN	635

Note: FDN is a Formaldehyde-based Naphthalene superplasticizer commonly used to improve the workability and strength of concrete.

Table 8. Nine types of Chinese commercial concrete price list.

Concrete type	C25	C30	C35	C40	C45	C50	C55	C60	C70
Cost(¥RMB/m^3)	447.5	457.5	472.5	487.5	502.5	517.5	532.5	547.5	587.5

Table 9. SWRL rules for the total cost of the beam.

SWRL rules for the total cost of the beam
Beams(?B)^Volume(?B,?BV)^ hasReinforcedConcrete(?B,?RC)^ReinforcedConcrete(?RC) ^Cost(?RC,?RCCost)^swrlb:multiply(?BTotalCost,?BV,?RCCost)->TotalCost(?B,?BTotalCost)

are shown in Table 8. Costing is carried out using the simple method in (4) below; its SWRL rules are represented in Table 9.

$$\mathrm{Cost} = \sum_{i=1}^{n} W_i \times Cost_i \tag{4}$$

W_i is the unit volume weight (kg/m^3), $Cost_i$ represent the cost per square meter (¥CNY/ m^3)

(3) Optimization method

In this case, optimization knowledge was also introduced to assist engineers in making decisions among multiple design options. Optimization knowledge includes the objectives, variables, and functions of the optimization. In this case study, a linear optimization method is e adopted, the optimization objective function is (5):

$$F(x_1, x_2, x_3) = A_1 f_{(\mathrm{safe})} + A_2 f_{(\mathrm{Energy\ consumption})} + A_3 f_{(\mathrm{cost})} \tag{5}$$

In this case study, the constraint of optimization function is the bridge structure's safety, including the maximum deflection and crack width. The optimization variables are x_1, x_2, x_3. x_1 is the cross-sectional area of the bridge, x_2 is a concrete type, x_3 are types of reinforcement. A_1,A_2 and A_3 are weight coefficients that can be adjusted according to the designer's requirements. For example, when the engineer's design requirements focus more on cost, its weight coefficient will be adjusted higher.

Due to the differing magnitudes of parameters such as cost, carbon emissions, and safety, it is necessary to apply normalization before performing linear optimization. The normalization method is shown below:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{6}$$

Where: x' is the normalized value, typically within the range [0,1], x is the original data value; x_{min} is the minimum value of the data, x_{max} is the maximum value of the data

The linear optimization calculations are embedded into the ontology model using SWRL rules. The bridge designer can get the optimal design solution by the design weight coefficient, thus avoiding decision uncertainty. These rules extract safety, sustainability, and cost outcomes from different design schemes, followed by normalization and linear optimization calculations. The SWRL rules governing this process are presented in Table 10.

Input design requirements

The design requirements are outlined in Table 11. The user inputs the standard span, calculated span, deck width, design load, and other requirements into the Interactive Web Service, as illustrated in Figure 7.

Table 10. SWRL rules for optimal calculation.

Normalization of costs:
Beams(?B)^TotalCost(?B,?BTotalCost)^has_Linear_Objective_Function(?B,?LOF)
^Linear_Objective_Function(?LOF)
^Cost_max(?LOF,?LOFCm)^O1(?LOF,?LOFO1)
^swrlb:divide(?BTotalCost1,?BTotalCost,?LOFCm)
^swrlb:multiply(?BO_F1,?LOFO1,?BTotalCost1) – >O_F1(?B,?BO_F1)
Normalization of carbon emissions:
Beams(?B)^TotalCO2(?B,?BTotalCO2)^has_Linear_Objective_Function(?B,?LOF)
^Linear_Objective_Function(?LOF)
^O2(?LOF,?LOFO2)^CO2_max(?LOF,?LOFC)
^swrlb:divide(?BTotalCO21,?BTotalCO2,?LOFC)
^swrlb:multiply(?BO_F2,?LOFO2,?BTotalCO21) – >O_F2(?B,?BO_F2)
Normalization of maximum displacement:
Beams(?B)^fc(?B,?Bfc)^has_Linear_Objective_Function(?B,?LOF)^Linear_Objective_Function(?LOF)
^O3(?LOF,?LOFO3)^fc_max(?LOF,?LOFfc)^swrlb:divide(?Bfc1,?Bfc,?LOFfc)
^swrlb:multiply(?BO_F3,?LOFO3,?Bfc1)
– >O_F3(?B,?BO_F3)
Normalization to maximum crack widths:
Beams(?B)^wfk(?B,?Bwfk)^has_Linear_Objective_Function(?B,?LOF)
^Linear_Objective_Function(?LOF)
^O3(?LOF,?LOFO3)^wfk_max(?LOF,?LOFwfk)^swrlb:divide(?Bwfk1,?Bwfk,?LOFwfk)
^swrlb:multiply(?BO_F4,?LOFO3,?Bwfk1)->O_F4(?B,?BO_F4)
Linear optimization computation:
Beams(?B)^O_F1(?B,?BO_F1)^O_F2(?B,?BO_F2)^O_F3(?B,?BO_F3)^O_F4(?B,?BO_F4)
^swrlb:add(?BO_F,?BO_F1,?BO_F2,?BO_F3,?BO_F4)->O_F(?B,?BO_F)

Design results and comparison

The ontology model must be checked first before acquiring the design structure. In this case study, the Pellet reasoner is adopted for continuity checking and mining implicit logical relations and complex semantic rule reasoning. Pellet is an open-source Java-based OWL 2 reasoner. It incorporates optimizations for nominals, conjunctive query answering, and incremental reasoning. Figure 8 shows the consistency checking results, meaning the ontology model is without logical errors. Then, the design results for the different cross-section shape options and material types obtained by running the Pellet reasoner are shown in Figure 9. The design results include safety, cost, and sustainability metrics. The design results are exported and plotted as bar charts for comparison, as shown in Figure 10. Figure 10 (a) to (c) shows the performance of all the design alternatives that meet the design criteria regarding safety, cost, and carbon emission. Figure 11. compares the reasoning results that meet the design criteria and consider the designer's preference (Safety, carbon emissions, and costs are weighted at 0.2, 0.5, and 0.3, respectively). It can be seen that the S1 bridge option, C25 concrete, and R235 rebar are the most appropriate design solutions for this case study.

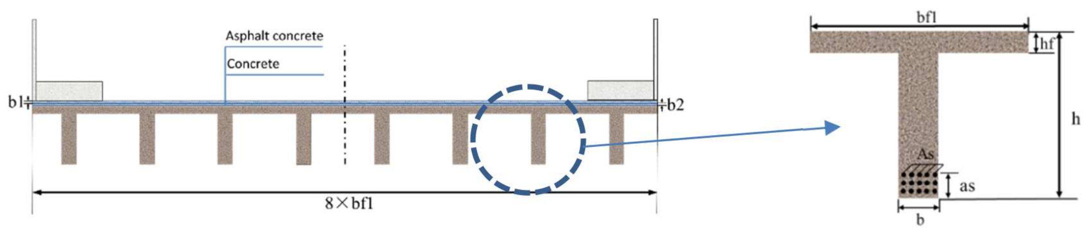
Extensibility validation

The functionality of ontology reuse and SWRL rules overlay provides excellent ontological scalability (Kersloot, van Putten, Abu-Hanna, Cornet, & Arts, 2020; Olivares-Alarcos et al., 2019). To verify the convenient expansibility of the system, the continuous beam bridge design function is expanded in the OntoDesign system. In this process, users must supplement the knowledge base and add new rules through the SWRL Tab. The details are shown in Table 12.

The reasoning computation is repeated after extending the ontology model and semantic rules, as shown in Figure 12. The parameters in the labeled boxes are the result of reasoning based on input parameters such as cross-section dimensions (b, h), deck width (h0), and span length (Length). The parameters in the marked boxes are reasoned results according to the input parameters such as cross-section dimensions (b, h), deck width (h0), and span length (Length). These

Table 11. Bridge design requirements in a case study.

Bridge Uses: The bridge does not have any social demand other than transportation demand.	
Span and deck width:	
Standard span	8m
Calculation span	7.6m
Bridge deck width	13m (traffic lane) +2*1.5 (sidewalk)
Technical standard:	
Design load	Highway – level 2
Environmental standards	First-class environment
Design safety level	Level 3
Main material:	
Beam	Concrete, steel bars
Bridge deck paving	0.04 m asphalt concrete、0.06 m concrete
Structure form: Simply supported beam bridge, Connected by 8 T-shaped beams with a width of 2 m.	
Bridge section:	



S1:bf1 = 2 m, h = 1.4 m, b = 0.3 m, as = 0.09 m, hf = 0.14 m, As = 15 × 0.02m
S2:bf1 = 2 m, h = 1.4 m, b = 0.3 m, as = 0.09 m, hf = 0.2 m, As = 15 × 0.02m

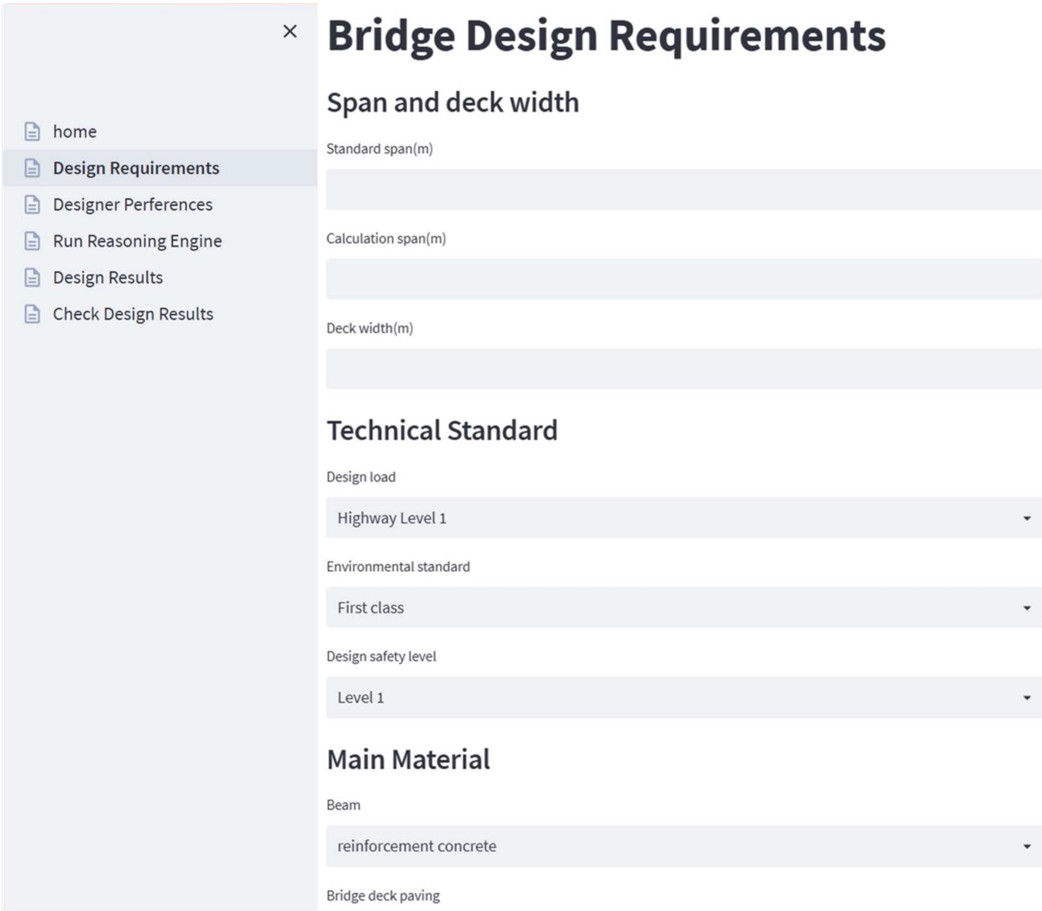


Figure 7. Input design requirements via interactive web service.

Table 12. System expansion details.

System needs	Design system development content	Continuous beam system expansion content
Part1 Information model	Class	No need to add
	property	No need to add
	instance	Need to add or modify.
Part 2 SWRL rules	Permanent action concentration	No need to add
	Maximum moment	Need to re-add
	The variable action effect causes a maximum moment	Need to re-add
	Total moment	No need to add
	Reinforced concrete section stress	No need to add
	Deflection calculation	No need to add
	Embodied carbon energy calculation	No need to add
	cost calculation	No need to add
	Optimal equation calculation	No need to add
Part 3 SQWRL rules	Choose plans that meet the requirements of the specification	No need to add
	Select the optimization equation result	No need to add

results include various design outcomes under this scheme, such as 'fc' representing displacement, 'TotalCO2' indicating carbon emissions, and 'TotalCost' representing cost.

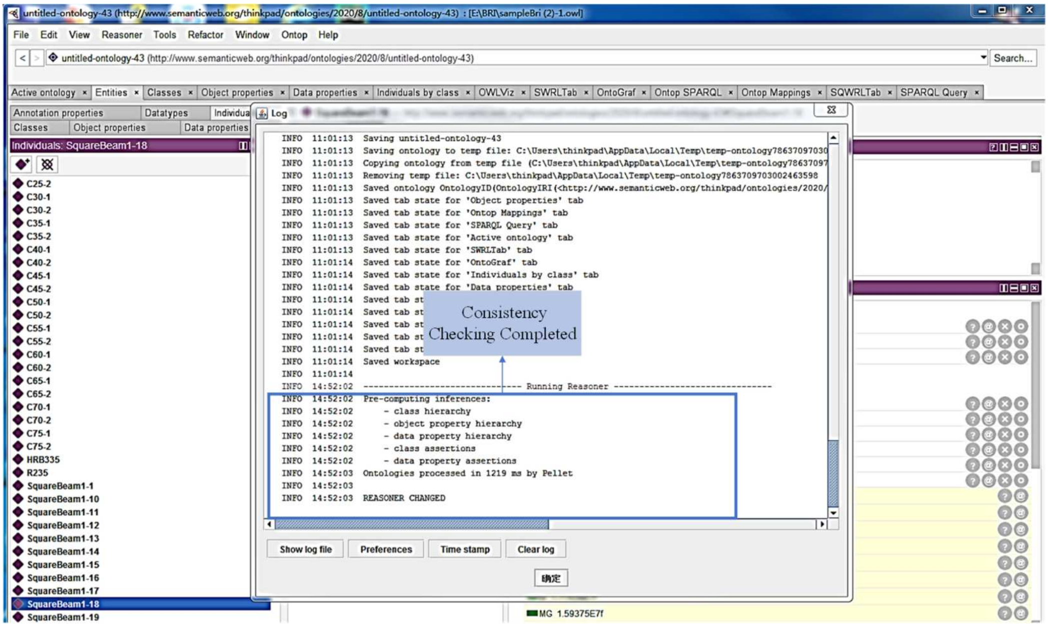


Figure 8. The log of consistency check.

Figure 9. Reasoning results are shown in Protégé.

Discission

As an initial attempt to implement an interactive, self-contained, and compliant structure design based on ontology, this case study demonstrates a general method for integrating C&S, cost, and

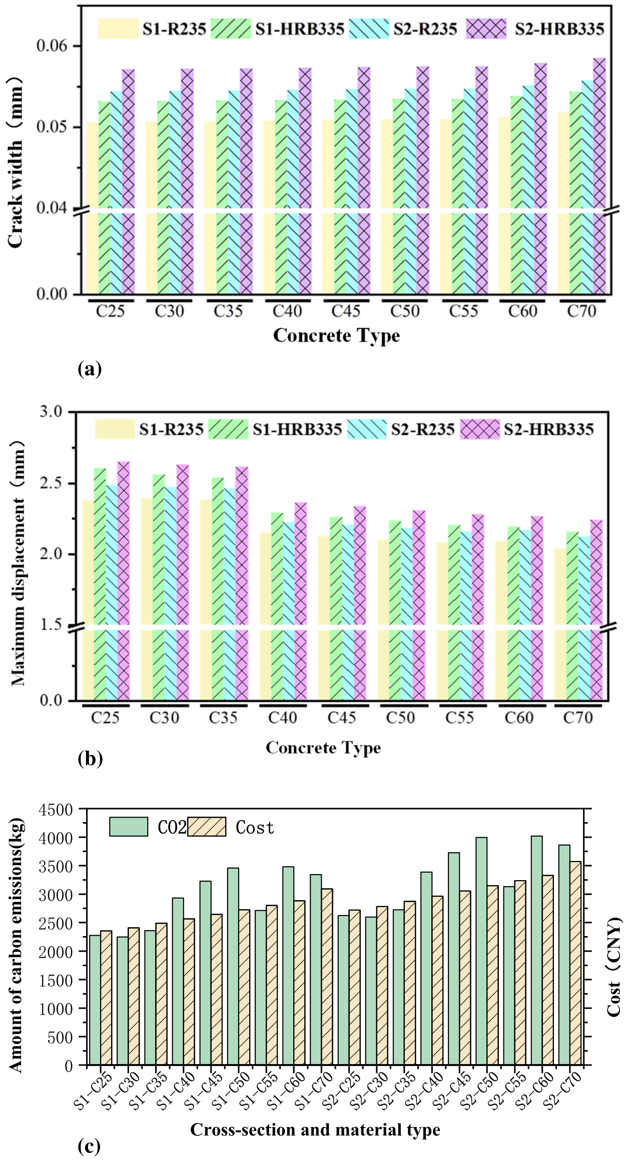


Figure 10. Comparison of results. (a) Safety calculation result – crack width. (b) Safety calculation result – bridge maximum displacement. (c) Calculation results of embodied carbon energy and cost.

carbon emissions into the ontology model. It highlights the advantages of the basic ontology-based structural design approach in terms of efficiency (with inference speeds at the millisecond level) and its ability to accommodate multiple objectives.

In large-scale designs, ontology-based methods show more significant potential compared to parametric methods and ML-based multi-objective design methods for the following reasons:

First, as seen in the extensibility verification case, ontology-based semantic reasoning is more flexible in accommodating changes in design constraints and rules (e.g. design requirements from standards or regulations). In contrast, traditional design tools are typically limited to specific objectives and constraints, with less adaptability.

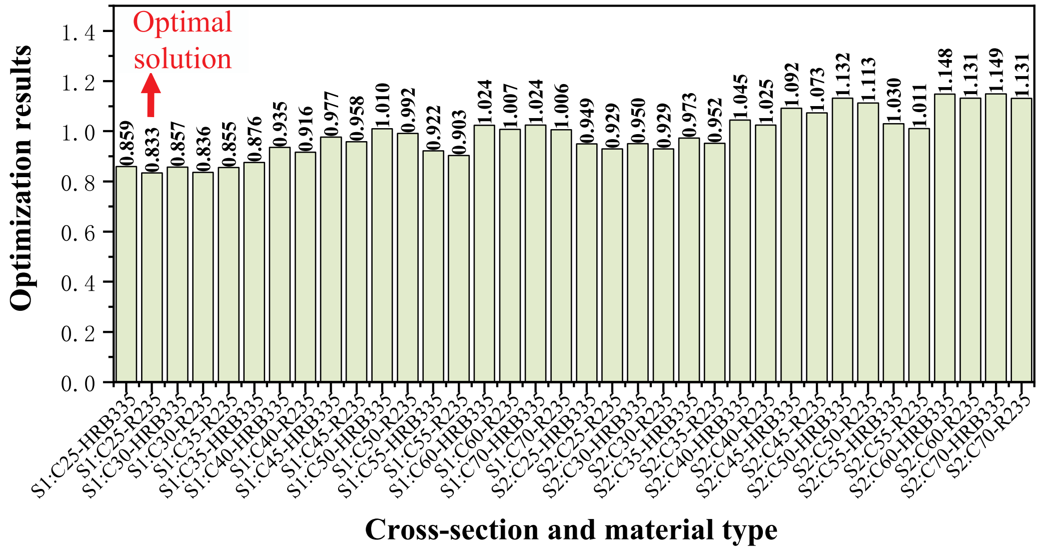


Figure 11. Comparison of multi-objective optimization function calculation results.

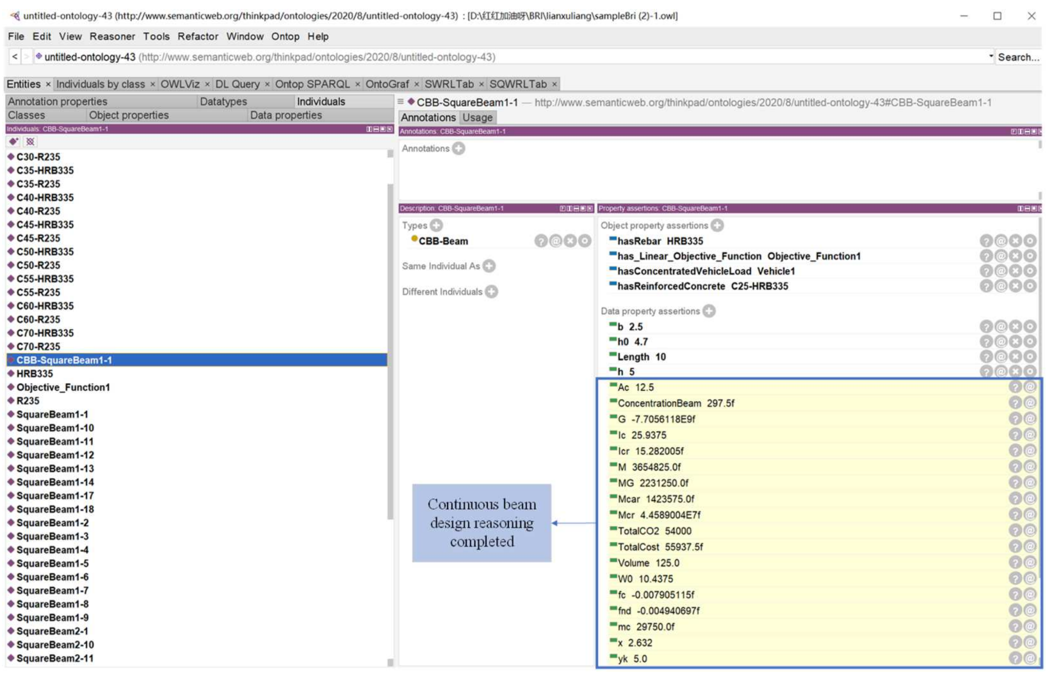


Figure 12. Inferred facts based on existing facts for continuous beam design.

Second, ontology-based structural design approaches offer the potential for collaborative functionality, enabling all design teams to use a unified knowledge representation method. By employing a standardized semantic model, ontology clarifies the relationships between different design concepts, rules, and regulations, ensuring that all teams operate with a common semantic understanding. In large-scale design projects, this unified knowledge-sharing mechanism can significantly enhance the consistency of information across teams and departments, reducing design conflicts caused by miscommunication. For instance, if the structural design proposed by one team contradicts the environmental requirements set by another, the system can immediately detect this conflict through reasoning and provide resolution suggestions. This automated conflict detection and resolution capability can significantly improve the efficiency of multi-team collaboration, reducing design iterations and errors.

Furthermore, ontology can unify the semantic modeling of design standards, specifications, parameters, and rules across different tools and software. By standardizing semantic representations, ontology can overcome data format barriers between various tools, facilitating data exchange and sharing among design software. For example, widely used structural design software such as SAP2000, ETABS, and Revit can be integrated with the ontology via interfaces, ensuring that the data structures and standards in the design models are uniformly represented across all platforms.

Conclusion

This paper proposed a self-contained and compliant multi-objective structural design framework based on an ontology that integrates multiple domain knowledge from design C&S, cost, and carbon emission. The main contributions are as follows:

Firstly, this study proposed an ontology-based knowledge mapping method to transform various types of unstructured knowledge into structured knowledge, integrating C&S with multi-domain knowledge into a unified knowledge representation. The framework ensures that the design results maintain a balance between multiple objectives and automatically comply with C&S. By converting fragmented and static codes and standards into a dynamic and intelligent knowledge system, the proposed approach not only significantly enhances the efficiency and accuracy of structural design but also provides robust technical support for lifecycle management, cross-disciplinary collaboration, and innovative decision-making in the construction industry, thereby driving the sector toward greater intelligence and efficiency.

Moreover, the ontology, seamlessly integrated as a backend service, enables interactive design by allowing engineers to query and achieve their design objectives. Through rigorous testing in multiple case studies, the developed system demonstrates its capacity to assist structural engineers in generating comprehensive design options and identifying the most suitable solutions.

In future work, we aim to enable the enhancement of the multi-objective optimization module to improve the ability of the ontology to solve complex optimization problems with the help of Artificial Intelligence methods. In addition, we will extend the scope of the ontology to encompass applications such as Environmental Impact Assessment (EIA) and Life Cycle Analysis (LCA). Using a modular ontology design, EIA and LCA knowledge will be integrated into the system, and the relationships between these domains and structural design objectives will be established. Additionally, multi-source data integration techniques will be employed to consolidate the diverse data involved in EIA and LCA, such as life cycle databases and environmental impact factors. This extension will enhance the system's capability in sustainability assessment and enable designers to identify potential environmental and social impacts at the early stages of design. Consequently, it will contribute to further optimization of design solutions, promoting the development of green buildings and infrastructure.

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