buildings

Article

A Knowledge Graph-Based Approach to Recommending Low-Carbon Construction Schemes of Bridges

Zhonggang Ma [1,2,3], Siteng Zhang [4], He Jia [1,2,*], Kuan Liu [1,2], Xiaofei Xie [3] and Yuanchuang Qu [5]

1 State Key Laboratory of Hydraulic Engineering Simulation and Safety, Tianjin University, Tianjin 300072, China; mazhonggang.cscec3b@foxmail.com (Z.M.); liukuan@tju.edu.cn (K.L.)
2 School of Civil Engineering, Tianjin University, Tianjin 300072, China
3 China Construction Third Engineering Bureau Group, Infrastructure Construction Investment Co., Ltd., Wuhan 300222, China
4 China Architectural Design and Research Institute Co., Ltd., Beijing 100044, China
5 North China Municipal Engineering Design & Research Institute Co., Ltd., Tianjin 300074, China
* Correspondence: jiahe_1130@tju.edu.cn

Abstract: With the development of the engineering construction industry, knowledge became an important strategic resource for construction enterprises, and knowledge graphs are an effective method for knowledge management. In the context of peak carbon dioxide emissions and carbon neutrality, low carbon emission became one of the important indicators for the selection of construction schemes, and knowledge management research related to low carbon construction must be performed. This study investigated a method of incorporating low-carbon construction knowledge into the bridge construction scheme knowledge graph construction process and proposed a bridge construction scheme recommendation method that considers carbon emission constraints based on the knowledge graph and similarity calculation. First, to solve the problem of the poor fitting effect of model parameters caused by less annotation of the corpus in the bridge construction field, an improved entity recognition model was proposed for low-resource conditions with limited data. A knowledge graph of low carbon construction schemes for bridges was constructed using a small sample dataset. Then, based on the construction of this knowledge graph, the entities and relationships related to construction schemes were obtained, and the comprehensive similarity of bridge construction schemes was calculated by combining the similarity calculation principle to realize the recommendation of bridge construction schemes under different constraints. Experiments on the constructed bridge low carbon construction scheme dataset showed that the proposed model achieved good accuracy with named entity recognition tasks. The comparative analysis with the construction scheme of the project verified the validity of the proposed construction scheme considering carbon emission constraints, which can provide support for the decision of the low-carbon construction scheme of bridges.

Keywords: knowledge graph; scheme recommendation; bridge construction scheme; low carbon construction; knowledge management

check for updates

Citation: Ma, Z.; Zhang, S.; Jia, H.; Liu, K.; Xie, X.; Qu, Y. A Knowledge Graph-Based Approach to Recommending Low-Carbon Construction Schemes of Bridges. *Buildings* **2023**, *13*, 1352. https://doi.org/10.3390/buildings13051352

Academic Editor: Jeong-Hoon Lee

Received: 26 March 2023
Revised: 16 May 2023
Accepted: 19 May 2023
Published: 22 May 2023

1. Introduction

Determining a suitable construction scheme is the most critical preparation task in the early stages of an engineering project. How to effectively use existing engineering case data and empirical knowledge to provide decision support for construction schemes for engineers is an important issue. As a key element of the construction organization design, the construction scheme of the primary bridge project directly affects the construction efficiency and economic benefits. However, the determination of the construction schemes of the existing bridge project relies heavily on experienced engineers and managers, which result in the lack of a systematic summary about engineering knowledge in the decision-making process. Additionally, carbon footprint and carbon emissions as hot words frequently appear in the public eye, attracting scholars to carry out research on the assessment and analysis of carbon emissions of buildings. Ref. [1] focused on possible approaches to reduce carbon emissions about low-carbon materials in construction sector for achieving the goal of control climate change. A study of office buildings showed that steel structures have a certain carbon emission advantage over concrete alternatives [2]. In the field of infrastructure, there were relevant research results on carbon emission estimation methods [3]. Concurrently, as a resource and energy-consuming infrastructure facility, bridges are characterized by high energy consumption, high carbon emissions and high resource consumption throughout their life cycle, particularly during construction. Researches on carbon emissions of bridges includes incorporating 3D bridge model information with carbon footprint analysis for lifecycle management [4], estimating the carbon footprint of bridges to analyze show the trends for different bridge materials and spans [5], using a life-cycle assessment method to analyze environmental impact [6]. Ref. [7] established carbon cost calculation model for the bridge in the construction stage. To complete bridge infrastructure construction in a high-quality, efficient, low-carbon and safe manner, research on methods and technologies that can organize the use of knowledge resources and guide bridge construction in the direction of green, low-carbon, energy-saving and emission reduction is required.

In 2012, Google formally introduced the concept of a knowledge graph, which is a semantic network that describes the relationships between entities and allows for a structured representation of facts such as things generated in the real world and their related relationships, which are typically defined as a collection of entities and relationships. Knowledge graphs can be divided into generic and domain knowledge graphs. Generic knowledge graphs are widely used, but the process of building them is difficult and complex. Generic knowledge graphs are also generally built by large internet enterprises from massive amounts of data [8]. Conversely, domain knowledge graphs are oriented toward domain-specific knowledge requirements and require only domain-specific knowledge for the construction of knowledge graphs, and are thus less difficult to build [9]. Although the construction of domain knowledge graphs is currently focused on popular fields such as finance, health care and education, research related to knowledge graphs in the field of engineering construction was also performed. Ref. [10] constructed a domain knowledge graph for shield construction projects and applied transfer learning algorithms to the adaptive transfer of construction project knowledge. Liu T et al. [11] proposed a hybrid BERT-BiLSTM model that combined a bidirectional encoder representation from transformers model (BERT) and bidirectional long-short term memory model (BiLSTM) for the textual intelligence analysis of water construction accidents, which provided algorithmic support and a basis for the analysis and decision-making of water construction accidents. Ref. [12] used entity identification and relationship extraction in power safety hazard records to construct a knowledge graph of power safety hazards that can quickly locate hazard sites based on intelligent reasoning model hazard equipment types and hazard phenomena in power safety hazard scenarios. As shown in existing studies, knowledge graph technology has good application prospects in the engineering field as a new method of knowledge management. However, due to certain variabilities of knowledge contents involved in different fields, specific methods and processes for processing knowledge are different.

In the field of civil engineering, there are also knowledge-based related research and applications, Ref. [13] developed a knowledge-based risk management tool via case-based reasoning (CBR) to capture, store, retrieve, and disseminate risk-related knowledge. Ref. [14] compared the relative capabilities of different surrogate modeling techniques to directly estimate seismic losses and explained advantages and disadvantages of knowledge-based surrogate models. In the literature about knowledge graphs in bridge engineering construction, Yang JX et al. [15] proposed an intelligent ontology model of bridge management and maintenance information based on semantic ontology; used the industry foundation classes (IFC) standard to express bridge structural units and management and maintenance information; analyzed the information conversion mechanism of IFC and ontology wed language (OWL); and established an information conversion framework. Ref. [16] proposed a knowledge graph construction method in the bridge inspection domain using a joint model based on a transformer encoder, bidirectional long- and short-term memory (BiLSTM) network and conditional random field (CRF) for named entity recognition and relationship extraction. However, no study investigated the application of knowledge graphs to low-carbon construction aspects of bridge engineering. Because a lot of project knowledge experience in the bridge construction field is scattered across various engineering and construction units without systematic collation, the lack of public corpus datasets leads to difficulty in constructing bridge construction scheme knowledge graphs. Thus, the effect of drawing on different domain models for entity recognition and relationship extraction in low-resource conditions is limited by the small amount of training data, which can lead to poor performance problems [17]. In terms of low carbon-related research in the bridge construction field, there was a green low carbon bridge evaluation system [18], carbon intensity index for the entire life cycle of bridges [19], carbon emission model for bridges [20], green construction technology [21], etc. However, there is a lack of effective combination with knowledge management tools. Therefore, there is a need to combine methods for effective management of bridge low-carbon construction-related knowledge and establish a knowledge model of bridge construction schemes considering carbon emission constraints to provide knowledge support for decision-making to achieve intelligent construction of bridge projects.

This study, thus, analyzes the methods of extracting bridge construction scheme knowledge and low-carbon construction knowledge in the bridge construction domain, designs and implements entity recognition, relationship extraction and knowledge storage; and proposes an improved model of entity recognition to meet the needs of low-resource conditions. Based on constructing a bridge construction scheme knowledge graph, a bridge construction scheme recommendation process is established based on the similarity calculation. Combining the characteristics of engineering practice, bridge construction scheme recommendations are performed under carbon emission constraints, and carbon emission analysis is performed using low-carbon construction knowledge. Results are then compared with existing construction scheme decision analysis methods, providing a new solution for the intelligent application of low carbon intelligent construction of bridges.

2. Bridge Construction Schemes Knowledge Graph Construction

2.1. Knowledge of Low Carbon Bridge Construction

The bridge construction scheme must be prepared based on the technical level of the construction and the construction experiences, considering bridge engineering, demolition engineering, large earthwork engineering, monitoring engineering, drainage engineering and other divisional engineering. In particular, when solving various problems that occur during construction, technical staff will record in detail the description of the engineering situation of the problems and the solutions, which accumulates a wealth of knowledge and experience.

The knowledge resources accumulated by the technical staff of the construction unit all come from engineering practice activities, and the preparation of the corresponding construction documents can more accurately describe the knowledge value of the technical staff of each profession [22]. Table 1 shows an example of the bridge construction scheme knowledge on the inspection of steel trestle bridges in bridge construction. A lot of empirical knowledge in the construction scheme is implicit in the unstructured text, and an effective method for extracting the relevant entities, relationships and attributes of the construction scheme from the unstructured text and transforming them into empirical knowledge must be studied, which can provide basic support to improve the knowledge management and application of the construction plan in the bridge engineering field.

Table 1. Example of bridge construction scheme knowledge.

Check Item	Allowable Deviation	Method and Frequency of Inspection
Midline deviation of bridge deck (mm)	100	Total station: Check places 3 to 8
Bridge width (mm)	±50	Ruler: 3 to 5 pieces per hole
Bridge length (mm)	+500, −500	Total station, steel rule inspection
Connection between centerline of approach and centerline of bridge (mm)	30	Ruler: The centerline of the approach and the centerline of the bridge are, respectively extended to the long end of the bridge on both sides to compare their plane positions
Bridge head elevation connection (mm)	±50	Ruler: The centerline of the approach and the centerline of the bridge are, respectively extended to the long end of the bridge on both sides to compare their plane positions
Flatness (mm)	±10	3 m ruler: Measure 3 places × 3 feet every 100 m

In the context of carbon peaking and carbon neutrality, there is an urgent need to introduce the concepts of green and low carbon into bridge construction plans to provide guidance for the green and low carbon construction of bridge projects. The determination of a low carbon bridge construction scheme requires consideration of the carbon emission influencing factors, carbon emission calculation parameters, carbon emission calculation models and carbon emission calculation methods during the bridge construction process, all of which can be used as low carbon construction knowledge for knowledge management and as a knowledge base to better serve bridge carbon emission analysis and evaluation.

(1) Factors influencing carbon emissions from bridges

Starting from the carbon emission sources in the construction process of the bridge project in the materialization stage, by collecting relevant literature and combining with the actual situation of the engineering project, the influencing factors of carbon emission are summarized. In the study of prefabricated buildings, the influencing factors related to it were explored in detail and can be summarized as six potential factors: project overview; consumption of building materials; transportation and storage; energy consumption; construction organization and management; and carbon emissions in the materialization stage of the project [23]. The effects of carbon emission influence from a bridge construction scheme affects material selection, usage of low carbon materials, energy mix schemes, etc.

(2) Bridge Carbon Emission Calculation Model

Due to the difficulty of obtaining data on the operation, maintenance and disposal phases of bridge projects, the carbon calculation model for bridge projects in the production, transport and construction phases of materials and equipment can be calculated using emission factors. A basic model for accounting for carbon emissions in the building phase based on the emission factor approach [24] is as follows:

$$\text{Carbon emission} = \text{direct/indirect relevant data} \times \text{emission factor} \tag{1}$$

Carbon emissions in the production stage of building materials are equal to the sum of the carbon emissions of various construction materials in the production and manufacturing stages, and carbon emissions are calculated as the product of the consumption or cost of materials or equipment and its carbon emission factor.

2.2. Knowledge Graph Construction Process

Knowledge graphs are typically constructed in three ways: top-down, bottom-up and a mixture of the two [25]. Considering that the bridge engineering field is a low-resource research field with a lack of knowledge resources and a lack of high-quality structured datasets for construction schemes, this study used a bottom-up construction approach for the construction of bridge construction scheme knowledge graphs.

The construction framework of the bridge construction scheme knowledge map is shown in Figure 1. Unstructured text data such as the construction method, special construction scheme and construction organization design were selected as data sources, and the construction scheme knowledge graph was constructed with the help of natural language processing (NLP) technology, including knowledge extraction, knowledge storage and visualization and knowledge updating.

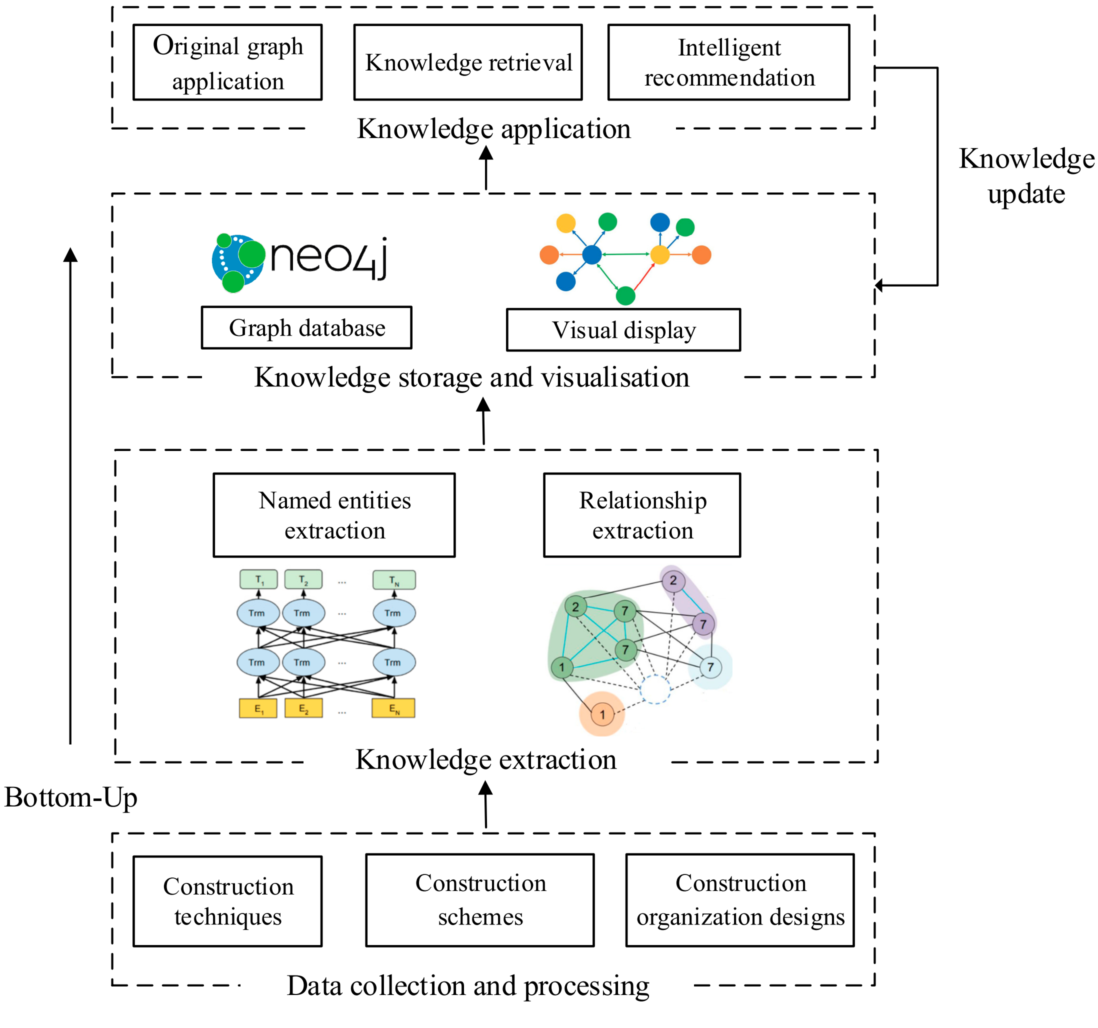


Figure 1. Knowledge graph framework for construction scheme.

2.2.1. Named Entity Recognition and Relationship Extraction

The effective extraction of entity-to-entity relationships from multisource text data is a key step in building a knowledge graph of a construction scheme. However, in the field of engineering construction, the relationship between entities is more complex and may exist not only implicitly in sentences but also between sentences, paragraphs and even across documents. Entity-to-entity relationships can be classified as one-to-one, one-to-many and many-to-many.

The bridge construction scheme contains many natural language text structure data and unstructured data, and the data must be preprocessed. For the training corpus, the first step is to annotate it, and this paper used the BIO annotation system to annotate the training corpus, with B-X representing the beginning of entity X, I-X representing the end of the entity, and O representing not belonging to any type. Table 2 shows some named entity categories of the knowledge graph of the bridge construction scheme combined with low carbon construction knowledge. For named entity recognition, the commonly used BERT-BiLSTM-CRF combination model, which is obtained by combining the existing BiLSTM with CRF and BERT, improved the original BiLSTM model feature extraction problem and enhanced the overall performance of the model [26].

Table 2. Named entity labels.

Serial Number	Type of Entity	Begin of Entity	Inside of Entity
1	Engineering projects	B-PRJ	I-PRJ
2	Divisional engineering	B-DIV	I-DIV
3	Construction schemes	B-NAM	I-NAM
4	Construction organizations	B-ORG	I-ORG
5	Construction technologies	B-TEC	I-TEC
6	Construction steps	B-STE	I-STE
7	Construction members	B-MEM	I-MEM
8	Construction machinery	B-MEC	I-MEC
9	Construction materials	B-MAT	I-MAT
10	Construction environment	B-ENV	I-ENV
11	Geological conditions	B-GEO	I-GEO
12	Construction risks	B-RIS	I-RIS
13	Carbon emission calculation methods	B-CME	I-CME
14	Carbon emission calculation rules	B-CRU	I-CRU
15	Carbon emission influencing factors	B-CFA	I-CFA
16	Carbon emission calculation parameters	B-CPA	I-CPA
17	Carbon emission factors	B-CEF	I-CEF
18	Carbon emissions	B-CEM	I-CEM
19	Nonphysical words	O	O

Relation extraction is the determination of corresponding semantic relations between entities obtained from text. Relationship extraction is usually built based on entity recognition. Given a sentence S, a triplet <v, r, t> containing three elements such as head entity v, relation r and tail entity t was extracted. According to the entity recognition definition of the bridge engineering construction scheme, the relationship classification between entities was performed, as shown in Table 3, which defines the correspondence between different entities of the low-carbon construction scheme. The CNN (convolutional neural network) algorithm is applied to extract the semantic features of the construction scheme entity relationships [27] and realize word vector representation, feature extraction and output in the field of bridge engineering.

2.2.2. Knowledge Graph Visual Presentation

For the storage of domain knowledge graphs, there are primarily relational databases, resource description frameworks (resource description framework, RDF), triples and graph databases in three ways [28]. Because there is a lot of relational information about entities and relationships in the knowledge graph, using a structured database for storage will generate a lot of redundant stored information; thus, using a graph database as a storage container for the knowledge graph becomes a popular choice. This study, thus, used the widely used Neo4j graph database, which is a high-performance graph database whose data storage structure usually contains nodes and relationships, where nodes are entities in the knowledge graph and each node corresponds to a label to distinguish different entity types, while entities also have their own attributes. Edges are semantic relationships between entities, which are also distinguished by a label and have their own properties.

Table 3. Semantic relationships between the entities.

Head Entity	Semantic Relations	Tail Entity
Engineering projects	Contains	Divisional engineering
Divisional engineering	Used	Construction schemes
Divisional engineering	In	Construction environment
Construction schemes	Need	Construction technologies
Construction schemes	Applications	Construction steps
Construction schemes	Suitable for	Construction environment
Construction schemes	Staffing	Construction members
Construction schemes	Equipment configuration	Construction machinery
Construction schemes	Material configuration	Construction materials
Construction members	Belongs to	Construction organizations
Geological conditions	Consider	Construction schemes
Construction schemes	Risk	Construction risks
Construction schemes	Impact	Carbon emission influencing factors
Construction schemes	Methods	Carbon emission calculation method
Carbon emission calculation method	Based on	Carbon emission calculation rules
Carbon emission calculation method	Analysis	Carbon emission calculation parameters
Carbon emission calculation parameters	Corresponding	Carbon emission influencing factors

The CSV and JSON format files extracted from the construction scheme text are imported in bulk into the Neo4j graph database by generating nodes, inserting relationships and adding attributes. The nodes and edges can be manually manipulated with Cypher statements, and the imported data can be noise-reduced and verified to complete the construction of the knowledge graph. The process of constructing the Neo4j graph database is shown in Figure 2. Using the knowledge graph triad to describe knowledge, it is possible to link construction methods, construction schemes, construction organization designs and low carbon construction knowledge to visually represent the complex connections between entity nodes.

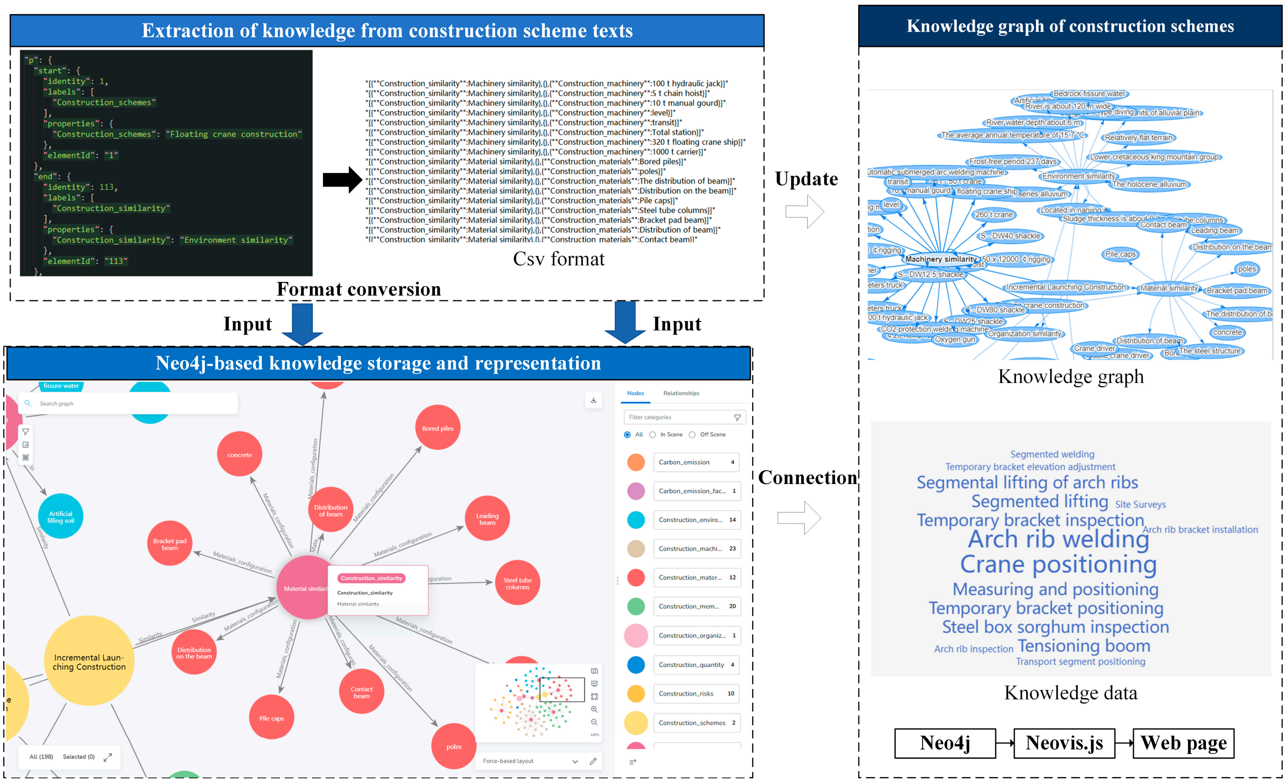


Figure 2. Neo4j-based knowledge graph visualization.

2.3. Low-Resource Knowledge Graph Construction

2.3.1. Low-Resource Named Entity Recognition

Most existing studies of knowledge graph construction assume that the entities or relationships in the knowledge graph have sufficient instances of triples to be trained to obtain a vector representation, thus requiring many manually annotated samples. However, in knowledge graphs of real-world conditions, many entities or relations have only a small number of triples; thus, there is a low resource problem [29]. In the bridge engineering domain, many relations have only a small training corpus, which makes it difficult to perform knowledge graph research in the bridge domain, and the low-resource problem in the bridge engineering domain can seriously limit the efficiency and performance of graph construction. With the continuous development of deep learning techniques, many deep learning methods were applied to low-resource named entity recognition tasks in recent years. Related research can be broadly classified into methods for cross-linguistic transfer [30], data enhancement [31] and integrating automatically annotated corpora [32].

These studies of low-resource knowledge graph construction methods primarily focused on English to Chinese data, insufficient annotation data and a lack of processing tools. Cross-language transfer and data enhancement methods can effectively alleviate the shortage of annotated corpora, but these methods are only applicable to languages with rich annotation resources. The integration of automatic annotation corpus methods often requires the development of domain-specific annotation tools, which are less applicable to different corpus contents and entity categories and cannot be fully applied directly. Because the Chinese dataset of low-carbon construction schemes in the bridge domain must be constructed, this study considered incorporating the Bernoulli distribution in the loss function of the BERT-BiLSTM-CRF model for improvement so that the model parameters can fit the data more accurately in low-resource conditions and proposes a more general low-resource named entity model to meet the need to construct the knowledge graph of low-carbon construction solutions in the bridge domain.

2.3.2. An Improved CRF-Based Entity Recognition Model

The improved CRF-based entity recognition model is a BERT-BiLSTM-CRF model that improves the CRF layer to improve model recognition. The original CRF layer is a model of the conditional probability distribution of another set of output sequences given a set of input sequences that is used to place restrictions on the labeled sequence outputs and can be represented by the representation $\mathrm{p}(y|x)$. Where the state characteristic transfer function can be represented in the model by a state transfer matrix, the final conditional probability obtained is:

$$\mathrm{p}(y|x) = \frac{1}{\mathrm{Z}(x)}\exp(w\varphi(x,y)) \tag{2}$$

$$\mathrm{Z}(x) = \sum_{y}\exp(w\varphi(x,y)) \tag{3}$$

where x and y are maps of a set of eigenvectors, which are the probability that the model obtains label sequence y under the condition of given text sequence x. The corresponding loss function is calculated as:

$$\mathrm{L}(w,x) = -\sum \mathrm{lgp}\left(y|x^{(\mathrm{i})},w\right) \tag{4}$$

The CRF method can also consider the sequence label dependencies, but under the low-resource condition limited by the size of the dataset, the parameter fitting of the model has difficulty achieving the expected effect, resulting in the output label sequence with the highest prediction probability not necessarily matching the real label sequence. To obtain a better entity recognition effect, a new loss function is constructed by incorporating the Bernoulli distribution into the conditional random field loss function [33], called the corresponding decoding model BCRF, to combine into a new BERT-BiLSTM-BCRF model by incorporating the Bernoulli distribution function into the CRF and adding a distribution function q to the original loss function calculation formula to construct a new loss function as follows:

$$q\left(y|x^{(i)},w\right)=\begin{cases}1, y\neq y*\\0, y=y*\end{cases}\tag{5}$$

$$L(w,x)=-\sum_{i}\lg\sum q\left(y|x^{(i)},w\right)p\left(y|x^{(i)},w\right)\tag{6}$$

The distribution function q equals 0 or 1 and is Bernoulli distributed. The *y** is the label that the model predicts with maximum probability, indicating the true label. In Formulas (1)–(6), when the predicted labels of words in the text message are consistent with the true labels, the loss value obtained is smaller, and conversely, if more predicted labels are incorrect in the text message, the loss is also larger. The structure of the improved BERT-BiLSTM-BCRF model is shown in Figure 3. The new loss function formulation was used for calculation, and the model parameters can be fitted better under low-resource conditions with a limited training annotated corpus.

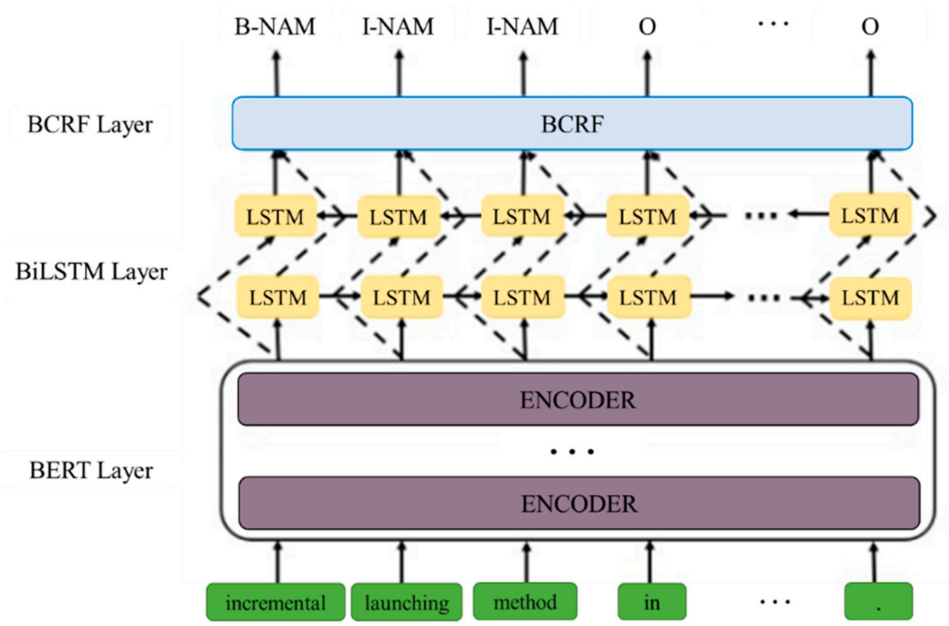


Figure 3. BERT-BiLSTM-BCRF model.

3. Knowledge Graph-Based Construction Solution Recommendations

3.1. Calculation of Construction Scheme Similarity

3.1.1. Comprehensive Similarity of the Construction Scheme

Entity similarity calculation can be used to measure the similarity of key features of the construction scheme entities such as different conditions and parameters, which is the key to entity matching and scheme recommendation [34]. Bridge project construction can be measured in several dimensions from constructors, machines, materials and the environment. Taking the construction scheme of a bridge project superstructure as an example, similarity can be analyzed in six dimensions: construction environment, construction unit, construction machinery, construction materials, construction members and construction risks.

The comprehensive similarity calculation of construction schemes based on knowledge graphs calculates the similarity of entities and relationships of different construction schemes read from the knowledge graph. The basic process is to obtain the key features of the construction scheme; use the entity matching methods such as attribute matching and neighbor information matching to calculate the entity similarity; obtain the influence weight of each entity class by setting different weight combinations; and finally weight the calculation to obtain the comprehensive similarity of the construction scheme. The process of calculating the similarity of construction schemes is shown in Figure 4.

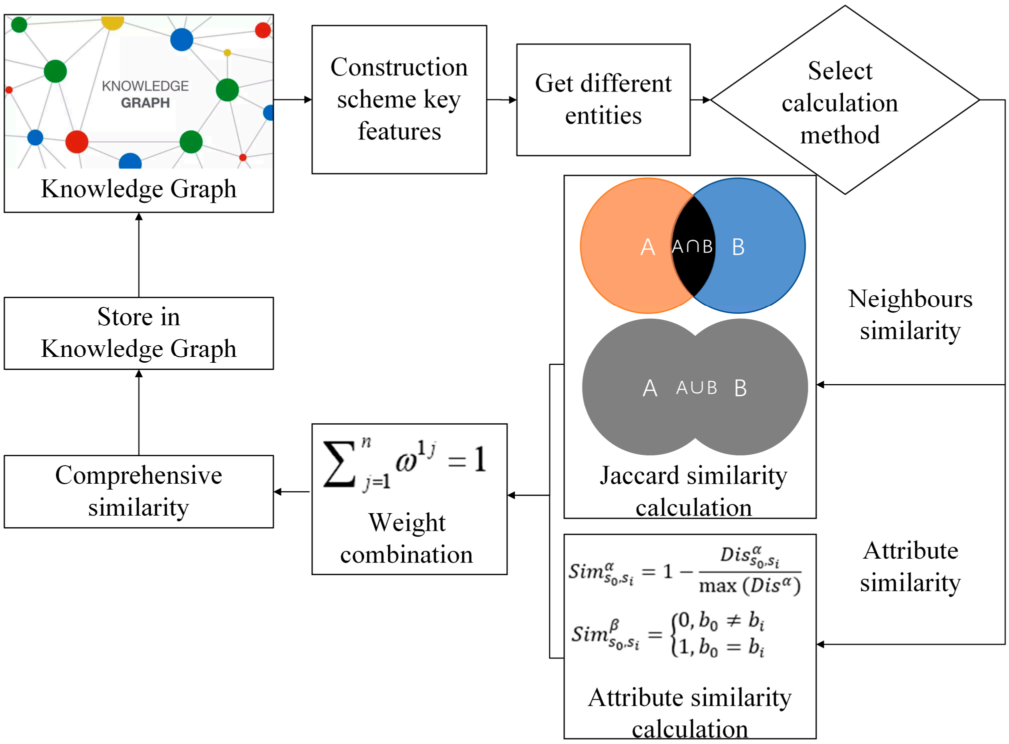


Figure 4. Comprehensive similarity calculation process.

3.1.2. Jaccard Similarity Calculation

When there is more than one entity corresponding to the entity class of a construction scheme, for example, when a construction scheme requires multiple configurations of materials, machines and members, the neighborhood matching method is used for calculation. The Jaccard similarity [35,36] coefficient is used to compare the similarity and difference between a finite set of samples. Given two sets A and B, the Jaccard coefficient is defined as the ratio of the size of the intersection of A and B to the size of the concurrent set of A and B, defined as follows:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{7}$$

where J(A,B) is defined to be 1 when sets A and B are both empty.

3.1.3. Attribute Similarity Calculation

When attributes are numeric, and by considering the distances of the attribute values and normalizing them, α is some numeric attribute, a_0 and a_i are the α attribute values for the two schemes, and the numeric attribute distances are defined as:

$$\mathrm{Dis}^{\alpha}_{s_0,s_i} = |a_0 - a_i| \tag{8}$$

The result after converting the distances into similarities and normalizing is as follows:

$$\mathrm{Sim}^{\alpha}_{s_0,s_i} = 1 - \frac{\mathrm{Dis}^{\alpha}_{s_0,s_i}}{\max(\mathrm{Dis}^{\alpha})} \tag{9}$$

where $\mathrm{Sim}^{\alpha}_{s_0,s_i}$ is the numerical attribute similarity of scenarios s_0 and s_i; $\mathrm{Dis}^{\alpha}_{s_0,s_i}$ is the numerical attribute distance of scenarios s_0 and s_i; and Dis^{α} is the set of values taken for the α numerical attribute distances.

When an attribute is a category, as defined below:

$$\mathrm{Sim}^{\beta}_{s_0,s_i} = \begin{cases} 0, b_0 \neq b_i \\ 1, b_0 = b_i \end{cases} \tag{10}$$

where $\mathrm{Sim}^{\beta}_{s_0,s_i}$ is the numerical attribute similarity between schemes s_0 and s_i; β is some numerical attribute; and b_0 and b_i are the β attribute values of the two scenarios.

3.2. Recommended Method for Low Carbon Bridge Construction Schemes

3.2.1. Recommended Process for Construction Schemes

The similarity-based construction case recommendation process determines the project engineering information and extracts the key features; retrieves the corresponding construction scheme cases [37]; considers the key features of the scheme corresponding to the entity class; and measures the similarity of the key features of the construction scheme, which calculates the comprehensive similarity of the construction solution based on the constructed bridge construction scheme knowledge graph. When the similarity does not reach the threshold, there are no similar construction schemes, and the construction scheme recommendation cannot be completed; when the similarity reaches the threshold, similar cases will be recommended according to their similarity values, a new construction scheme will be generated by modifying and reusing the cases, and the construction scheme knowledge graph can be updated. The specific process is shown in Figure 5.

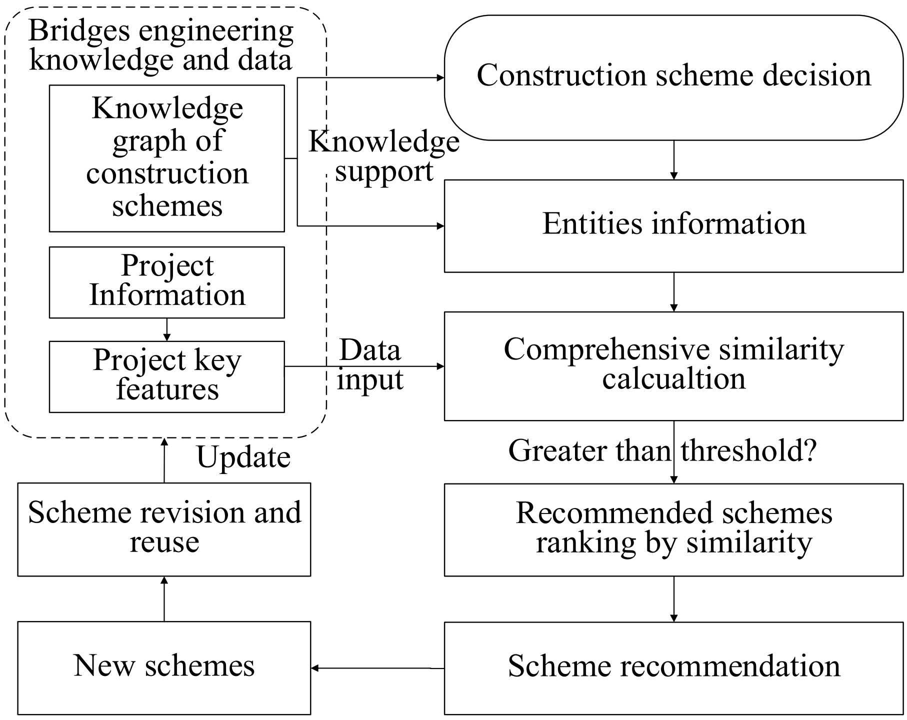


Figure 5. Similarity-based construction scheme recommendation process.

3.2.2. Recommended Construction Scheme Considering Carbon Emissions

The carbon emissions of various bridge construction schemes can be calculated by a carbon calculation model, which is used as a carbon emission indicator for the analysis and evaluation of the construction scheme. Taking the carbon emission analysis of the material and machine production phase of the construction scheme as an example, the types and quantities of the primary materials, energy and machines used are counted first, and the corresponding carbon emission analysis list is listed. By matching the component names in the parameter library and the inventory library, the carbon emission factors for energy, materials and labor in the basic database are linked and then combined with the carbon emission measurement model formulae and the corresponding calculation procedures, and the carbon emissions for the production phase of the material of different construction schemes are quickly calculated [38].

The calculated carbon emissions of the construction scheme measured by the carbon emissions calculation program are used as a low carbon indicator, combined with the similarity of the construction scheme, which can set limits on the carbon emissions measurement results to set constraints on the recommendation of the construction scheme. When performing the construction scheme similarity calculation, the carbon emissions are supplemented in the form of a (scheme, calculation result, carbon emissions) triad to the construction scheme knowledge graph, which can be calculated by matching numerical attributes between the carbon emissions of different schemes while supplementing with setting the corresponding weights to achieve the recommendation of low carbon bridge construction solutions considering the carbon emission indicator and using it as a constraint. The corresponding process is shown in Figure 6.

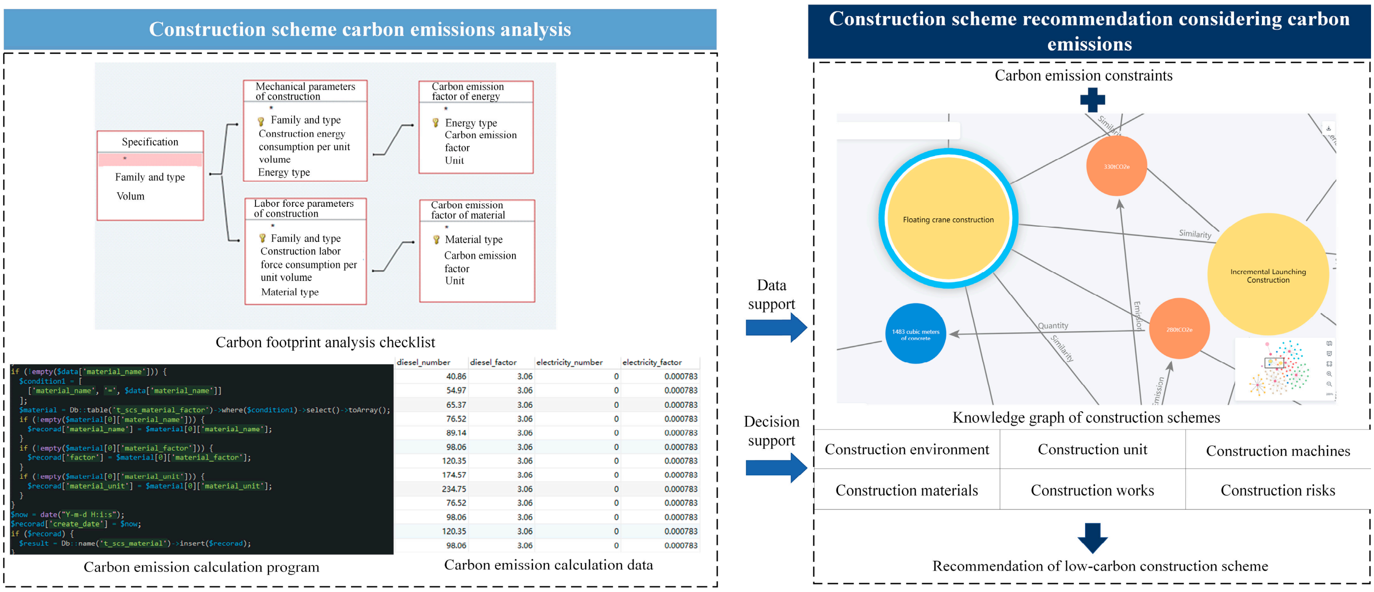


Figure 6. Recommended construction scheme considering carbon emissions.

4. Experiments and Applications

4.1. Dataset Production

Experimental data were primarily collected from the construction scheme information, technical delivery information, commercial information and measurement review information of the bridge construction projects, as well as the internet search for bridge superstructure construction method text information, bridge engineering special construction scheme text information and construction organization design text information. The dataset consisted of 27 bridge construction-related documents and 1 bridge carbon emission analysis report, with the help of a word dictionary to mark up the experimental text in batch. The process of construction dataset is shown in Figure 7, which contained 8 representative bridges built by China Construction Third Bureau Group Co., Ltd. using different construction schemes. By writing a Python program and compiling with Pycharm2021.2(Edu) software, read the corpus data in the document to achieve BIO annotation and obtain the dataset stored in the txt format file. The low-carbon construction aspect of the bridge includes knowledge of carbon emission factors, calculation criteria, calculation parameters and other low-carbon analysis in the field of bridge engineering, involving carbon emission factors including asphalt, diesel, petrol, concrete, steel and other common construction materials.

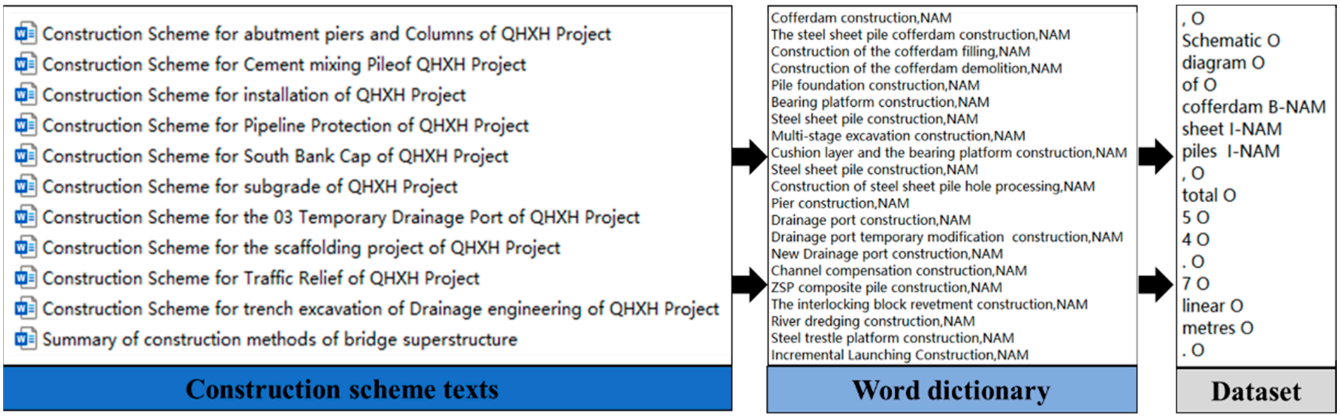


Figure 7. Process of Construction Dataset.

4.2. Experimental Analysis

(1) Evaluation indicators

Three metrics were used to evaluate the performance of the BERT-BiLSTM-BCRF model in entity recognition: Precision P Recall R (Recall), and F1 value. Precision is a measure of the accuracy of positive case prediction; recall is a measure of how many true positive cases the model can identify; the F1 value is the summed average of precision and recall, with F1 reaching its best value at 1 and its worst value at 0. The corresponding formula is as follows:

$$P = \frac{TP}{TP + FP} \tag{11}$$

$$R = \frac{TP}{TP + FN} \tag{12}$$

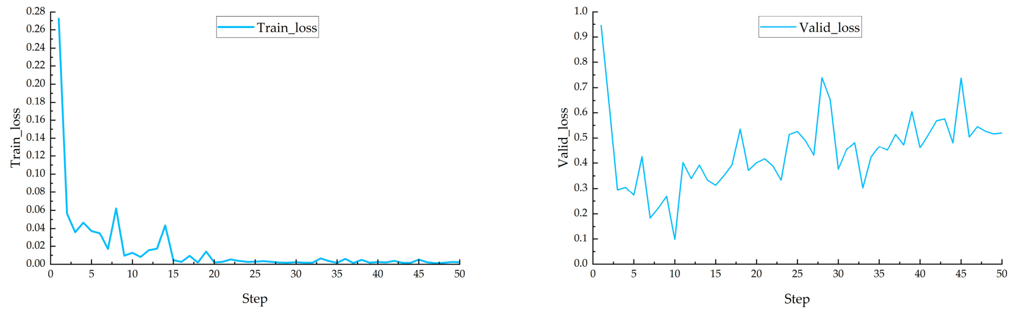
$$F1 = \frac{2PR}{P + R} \tag{13}$$

where TP (true positive) is the number of positive samples that are correctly identified; FP (false-positive) is the number of false-negative samples; TN (true negative) is the number of negative samples that are correctly identified; and FN (false-negative) is the number of positive samples missed.

(2) Experimental analysis

The dataset for this experiment was randomly divided into training, validation and testing datasets in a ratio of 8:1:1, which means 80% of the bridge construction scheme data were randomly selected for training the BERT-BiLSTM-BCRF model, 10% for validating the model and 10% for testing its performance. The primary hardware and software used to conduct the construction scheme entity recognition included the operating system Windows 10 Professional, an Intel(R) Core(TM) i7-8700 CPU operating @ 3.20 GHz CPU with 16 GB of RAM, the compilation platform Pycharm, the Python 3.8 programming language, and the open source library TensorFlow.

Taking the model training process with epoch = 50 and batch size = 64 as an example, the loss function changes during model training, as shown in Figure 8. It can be seen in Figure 8b the valid loss function curve fluctuated after being trained by 10 epochs, which indicates that the later epochs were overfitted. The optimal accuracy was reached in the 10th epoch and the final recognition effect of some entities on the bridge construction scheme dataset is shown in Table 4.



(**a**) train loss function curve (**b**) valid loss function curve

Figure 8. Model training process.

Table 4. Partial named entity recognition model identification results.

Entity Category	BERT-BiLSTM-BCRF			Number of Entities
	P	R	F1	
Divisional engineering	0.9563	0.9918	0.9737	486
Construction schemes	0.9683	0.9242	0.9457	66
Construction organizations	1.000	0.7143	0.8333	7
Construction technologies	0.9593	0.8519	0.9020	27
Construction steps	0.9630	1.000	0.9811	52
Construction machinery	0.9487	0.9250	0.9367	40
Construction materials	0.9869	0.9967	0.9918	302
Construction environment	0.9600	0.8276	0.8889	29
Average	0.9678	0.9039	0.9317	-

From the experimental performance results of the model shown in Table 5, the accuracy, recall and F1 values of the hybrid BERT-BiLSTM-BCRF model proposed in this study achieved good results during testing with the bridge construction scheme dataset. In particular, the weighted average F1 value reached 0.9317, indicating that the BERT-BiLSTM-BCRF model can identify multiple construction scheme type entities with high F1 values, indicating good prediction performance between the real and predicted labels.

Table 5. Carbon footprint comparison between different schemes.

Serial Number	Main Supplies	Quantities		Unit	Carbon Emission (tCO_2e)	
		Incremental Launching	Floating Crane		Incremental Launching	Floating Crane
1	Concrete	1245	1483	m^3	280.125	333.675
2	Steel	1124	970	t	2472.8	2134
Total					2752.925	2467.675

4.3. Knowledge Graph of Bridge Construction Schemes

By constructing the knowledge graph of the identified entities and relations, storing and visualizing them with the help of the Neo4j graph database, and fusing the triads extracted from the construction scheme, the obtained knowledge graph of the bridge construction scheme is shown in Figure 9. The relationship edge and the entities on both sides form knowledge. For example, the triad of nodes and edges <"cofferdam construction", "equipment configuration", "excavator"> shows that "cofferdam construction" is the construction scheme entity and "excavator" is the construction machinery entity, which expresses the knowledge that "the cofferdam construction scheme requires an excavator as the construction machine".

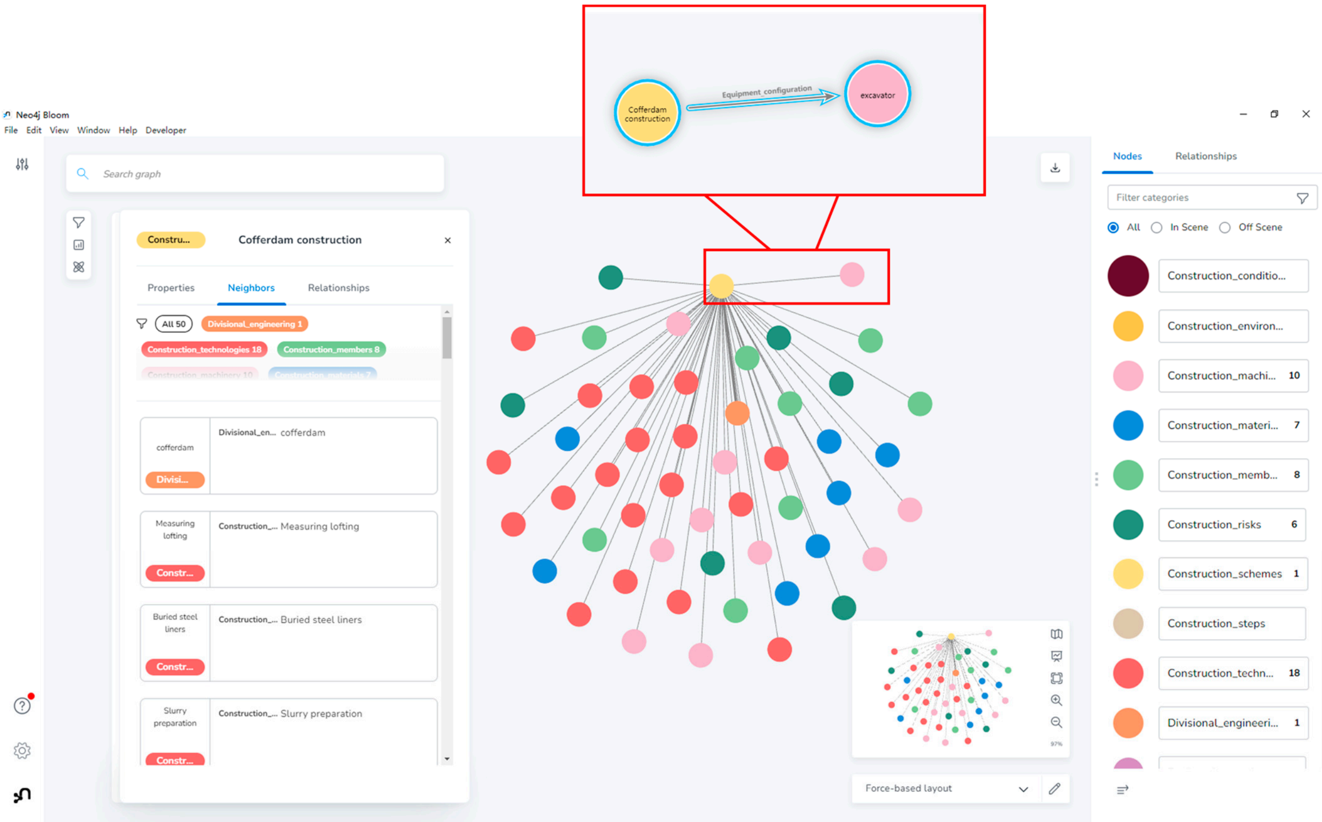


Figure 9. Example of a knowledge graph for a bridge construction scheme.

In addition to comprehensive consideration of bridge engineering in carbon peaking and carbon neutral backgrounds, the bridge construction knowledge graph is complemented for bridge construction carbon emission accounting methods, analysis standards, influencing factors, calculation parameters, carbon emission factors and other related knowledge to provide a reference basis for analyzing the green and low-carbon levels of bridge engineering. This process is also a preliminary exploration of the construction of a knowledge graph for low-carbon construction in the field of bridge engineering. Based on the bridge construction scheme knowledge graph in Figure 9, a bridge construction scheme carbon emission analysis knowledge network of construction scheme and carbon emission influencing factors, calculation methods, calculation standards, calculation parameters and corresponding carbon emission factors was constructed, as shown in Figure 10, to help project managers understand the steps and knowledge involved in carbon emission analysis and calculation of bridge construction schemes, and enhance the knowledge of low carbon bridge construction utilization and efficiency.

4.4. Recommended Construction Schemes under Carbon Emission Constraints

After completing the construction of the knowledge graph of the low-carbon bridge construction scheme, the corresponding construction scheme comprehensive similarity calculation program and the construction solution intelligent recommendation system page were developed. In the front-end page, the relevant engineering characteristics of the recommended construction schemes were input into the database and connected to the back-end calculation program. By reading the entities and relationships in the Neo4j database, different similarity calculation methods were used to match and calculate the entities related to the construction environment, construction units, construction machinery, construction materials, construction members and construction risks, and weights were set for each type of entity to obtain the construction schemes. The overall process is shown in Figure 11.

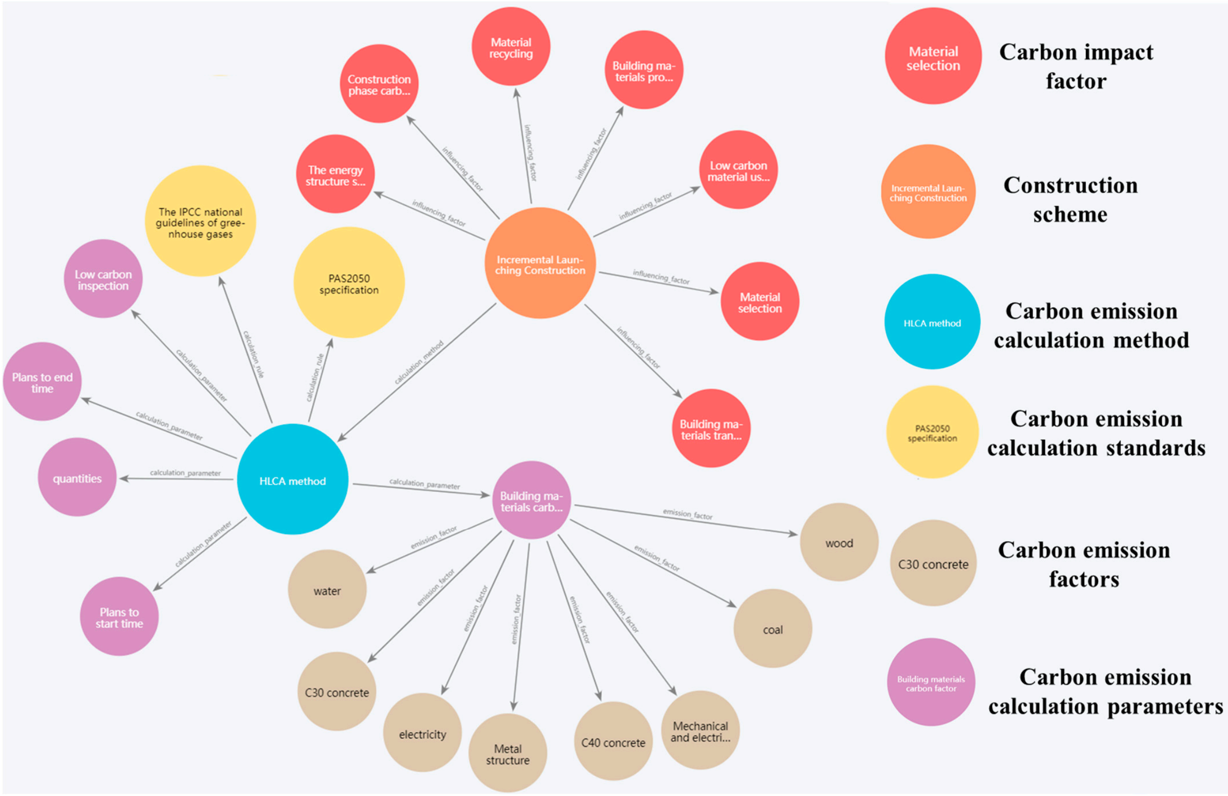


Figure 10. Example of a knowledge graph for bridge construction carbon emission analysis.

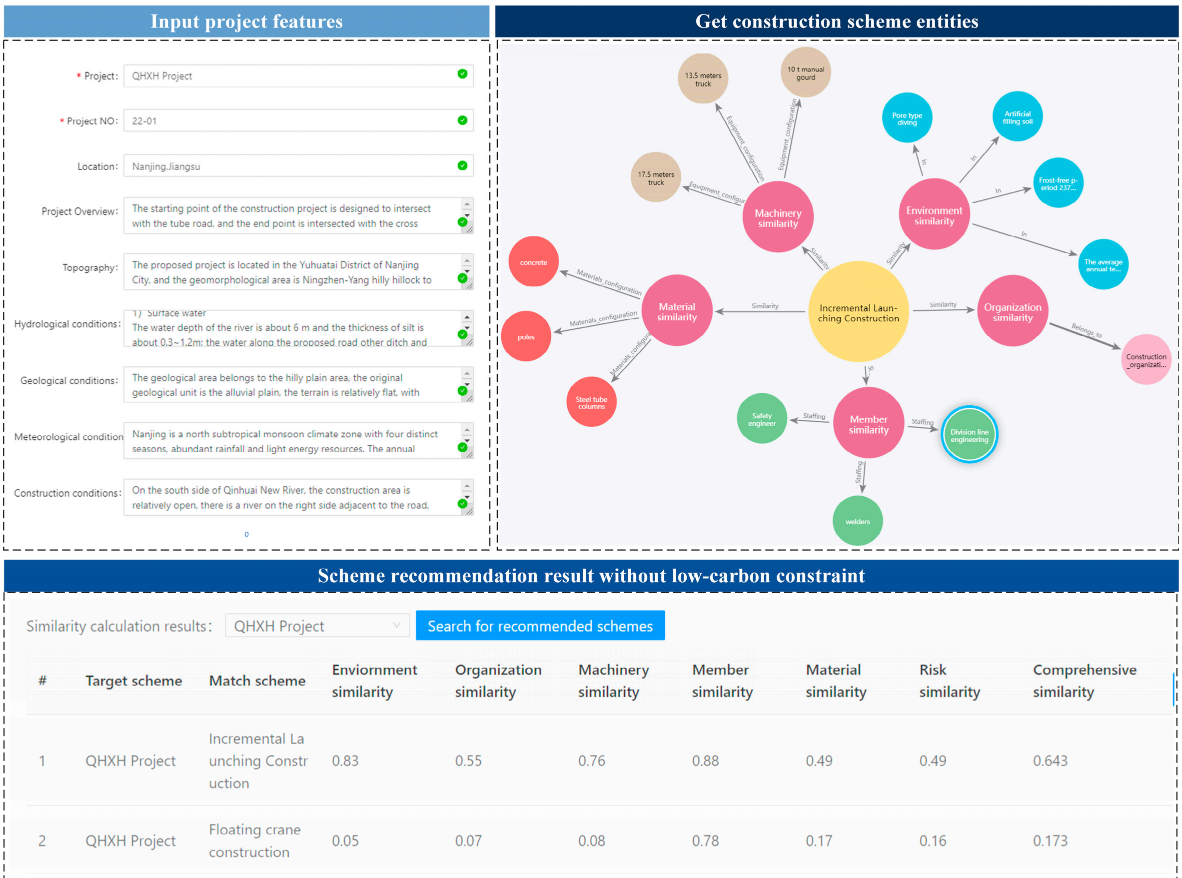
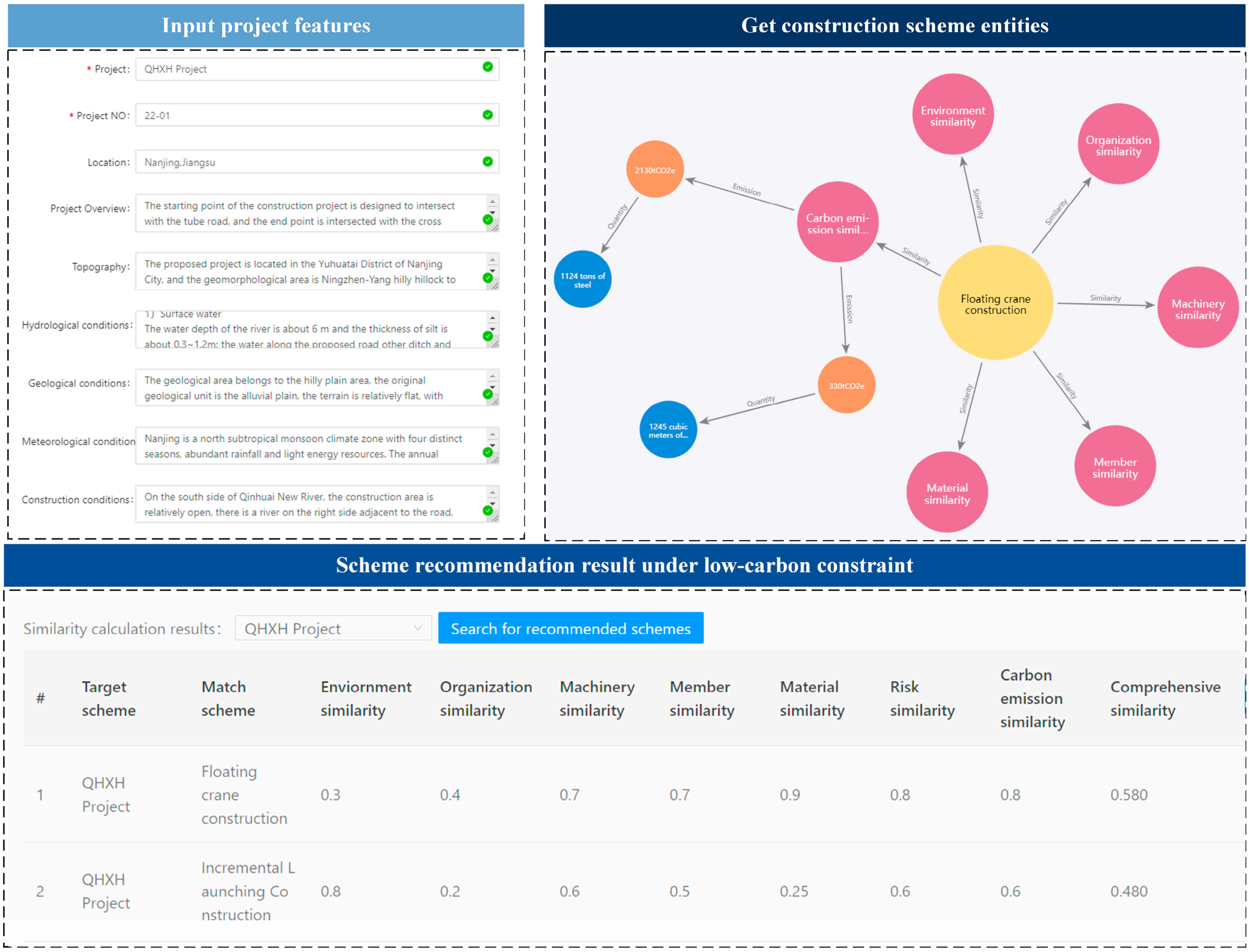


Figure 11. Recommended construction schemes without carbon emission constraints.

Similarly, when recommending construction schemes under carbon emission constraints, the carbon emission constraint was set when inputting engineering features, and the scheme recommendation process will add the entity similarity calculation on carbon emissions when performing similarity calculations through a knowledge graph. Then, the construction scheme recommendation considering carbon emissions will be obtained, and the recommendation result is shown in Figure 12.



#	Target scheme	Match scheme	Enviornment similarity	Organization similarity	Machinery similarity	Member similarity	Material similarity	Risk similarity	Carbon emission similarity	Comprehensive similarity
1	QHXH Project	Floating crane construction	0.3	0.4	0.7	0.7	0.9	0.8	0.8	0.580
2	QHXH Project	Incremental L aunching Co nstruction	0.8	0.2	0.6	0.5	0.25	0.6	0.6	0.480

Figure 12. Recommended construction schemes under carbon emission constraints.

4.5. Comparison of Construction Schemes

To ensure the reasonableness and accuracy of the recommended results of the construction scheme, carbon emission analysis and calculation were performed for the recommended results without carbon emission constraints and the recommended results with carbon emission constraints considered. According to the carbon emission calculation model, units such as steel and concrete were transformed as necessary and multiplied by the corresponding carbon emission factors to obtain a comparison of the carbon emissions and energy consumption obtained for the two construction options [39–42]. The results of the carbon emission analysis are shown in Table 5. Considering the carbon emissions of the different construction schemes, the construction of the floating crane scheme produced less carbon emissions, indicating that the floating crane construction option was more advantageous in terms of low carbon construction.

The project department aimed to complete the construction of the bridge superstructure with high quality, high efficiency and safety. Based on bidding documents, bidding reply, construction drawings, a construction contract and a survey of the project site, managers and engineers analyzed and compared decisions, as shown in Table 6.

Table 6. Comparative analysis of construction schemes without considering low carbon.

Schemes	Feasibility	Schedule Analysis	External Environmental Influences	Analysis of Measures
Incremental launching	Feasible	Overland assembly	Intermittent channel closure for 20 days for jacking work	Five sets of temporary piers are set up within the river, the rest of the piers and assembled supports are located on the river bank, which is less difficult to construct
Floating crane	Feasible	Floating assembly	Floating crane construction requires 95 days of intermittent cutoff	The assembled supports are all located within the river, making construction difficult

After a comparative analysis of the construction options with conventional low-carbon factors not being considered, it is more advantageous to use the floating crane construction scheme based on (1) a real analysis of the decision, which showed that using the incremental launching construction scheme is better; and (2) similarity calculations from the perspective of green low-carbon construction. Based on the bridge carbon emissions analysis and calculation of the floating crane construction scheme, 2467.675 tons of carbon dioxide is better than the incremental launching construction scheme, which verifies the reliability of the recommendation method.

Results also show that the traditional method of construction scheme decision analysis lacked a combination of green, low-carbon ecological and environmental protection concepts. Therefore, the research of bridge low-carbon construction scheme recommendation based on knowledge graphs conducted in this paper can provide decision-making for construction schemes from the knowledge management perspective by combining more bridge low-carbon construction knowledge during bridge engineering infrastructure construction and can provide a solution for green bridges from the perspective of improving the level of intelligent application. This study, thus, described a method of knowledge management and scheme recommendation solutions for the construction of green bridges that can improve the level of intelligent application and provides new ideas and methods for the comparison of bridge construction schemes in engineering projects.

5. Conclusions

This paper proposed a method for recommending bridge construction schemes based on a knowledge graph, which can recommend bridge construction schemes considering carbon emission constraints and assist in decision-making for bridge construction management. The primary findings of this study were as follows:

(1) This study proposed a method that combines knowledge graph technology with scheme recommendation; proposes new knowledge management tools to organize and use construction scheme knowledge and low-carbon knowledge in the bridge engineering field; supplements existing construction unit knowledge management tools; and improves the previous construction units' inability to fully incorporate carbon emissions when making construction decisions by considering construction scheme recommendations made under carbon emission constraints. This study also provided a new basis for decision-making and analysis by considering carbon constraints.

(2) The CRF model was improved by using a loss function that introduced the Bernoulli distribution to build a BCRF model layer and proposed a BERT-BiLSTM-BCRF model for low-resource entity recognition. Experiments were performed with the bridge construction scheme dataset, and experimental results showed that compared with the generic methods

of knowledge graphs in other fields, the proposed bridge construction scheme can be performed effectively with limited datasets. Results also validated the usefulness of the knowledge graph construction method in the low carbon bridge construction field.

(3) The similarity calculation method combined with the knowledge graph can perform the similarity calculation based on the entities and relationships in the knowledge graph, and by setting different combination weights, can recommend bridge construction schemes while considering carbon emission constraints. Recommendations from the proposed method were reasonable compared with traditional decision analysis without considering carbon emission constraints, which can promote the intelligent development of construction decisions in bridge construction. The proposed method can also provide a reference for the design and application of recommendation systems in the engineering field.

The results of this study provide information that can aid the search for and visualization of relevant knowledge, and future research should continue to improve bridge construction scheme knowledge by enriching and complementing the knowledge graph, which can provide more accurate service support for application scenarios such as original graph application, knowledge retrieval, knowledge Q&A and intelligent recommendation of the knowledge graph. This study also provided a comparison and selection for bridge construction scheme decisions and implementation in real engineering project construction.

Author Contributions: Conceptualization, Z.M.; methodology, Z.M. and S.Z.; software, Z.M., H.J. and K.L.; validation, X.X. and Y.Q.; formal analysis, S.Z. and H.J.; investigation, Z.M.; data curation, Z.M., X.X. and Y.Q.; writing—original draft preparation, Z.M., S.Z. and K.L.; writing—review and editing, Z.M., S.Z., H.J. and K.L.; visualization, H.J. and K.L.; supervision, Z.M., S.Z., H.J. and K.L.; project administration, Z.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data are not publicly available due to restrictions of privacy.

Acknowledgments: The authors would like to acknowledge Sherong Zhang, Chao Wang, Xiaohua Wang (Tianjin University) for valuable comments on this paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Orsini, F.; Marrone, P. Approaches for a low-carbon production of building materials: A review. *J. Clean. Prod.* **2019**, *241*, 118380. [CrossRef]
2. Esteghamati, M.Z.; Sharifnia, H.; Ton, D.; Asiatico, P.; Reichard, G.; Flint, M.M. Sustainable early design exploration of mid-rise office buildings with different subsystems using comparative life cycle assessment. *J. Build. Eng.* **2022**, *48*, 104004. [CrossRef]
3. Wang, X.; Duan, Z.; Wu, L.; Yang, D. Estimation of carbon dioxide emission in highway construction: A case study in southwest region of China. *J. Clean. Prod.* **2015**, *103*, 705–714. [CrossRef]
4. Collings, D. The Carbon Footprint of Bridges. *Struct. Eng. Int.* **2021**, *32*, 501–506. [CrossRef]
5. Kaewunruen, S.; Sresakoolchai, J.; Zhou, Z. Sustainability-based lifecycle management for bridge infrastructure using 6D BIM. *Sustainability* **2020**, *12*, 2436. [CrossRef]
6. Wang, J.; Pan, K.; Wang, C.; Liu, W.; Wei, J.; Guo, K.; Liu, Z. Integrated Carbon Emissions and Carbon Costs for Bridge Construction Projects Using Carbon Trading and Tax Systems—Taking Beijing as an Example. *Appl. Sci.* **2022**, *12*, 10589. [CrossRef]
7. Zhou, Z.W.; Alcalá, J.; Yepes, V. Bridge carbon emissions and driving factors based on a life-cycle assessment case study: Cable-stayed bridge over hun he river in liaoning, china. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5953. [CrossRef]
8. Meng, F.-J. Method and Practice of Domain Knowledge Graph Construction. Master's Thesis, Nanjing University, Nanjing, China, 2021.
9. Feng, J.; Hang, T.-T.; Chen, J.; Wang, Y.-F.; Wang, B.-F.; Zhang, T. Research status of domain knowledge graph and its application in water conservancy. *J. Hohai Univ. (Nat. Sci.)* **2021**, *49*, 26–34.
10. He, M.-Q. Research on Knowledge Transfer Model of Construction Projects Based on Knowledge Graph and Transfer Learning. Master's Thesis, Southwest Jiaotong University, Chengdu, China, 2021.
11. Liu, T.; Zhang, S.-R.; Wang, C.; Li, Z.-H.; Guan, W.; Wang, X.-H. Text intelligent analysis for hydraulic construction accidents based on BERT-BiLSTM hybrid model. *J. Hydroelectr. Eng.* **2022**, *41*, 1–12.

12. Qu, Z.-Y.; Zhang, Z.-M.; Liu, S.; Cao, J.; Bo, X.-Y. Knowledge-driven recognition methodology for electricity safety hazard scenarios. *Energy Rep.* **2022**, *8*, 10006–10016. [CrossRef]
13. Okudan, O.; Budayan, C.; Dikmen, I. A knowledge-based risk management tool for construction projects using case-based reasoning. *Expert Syst. Appl.* **2021**, *173*, 114776. [CrossRef]
14. Esteghamati, M.Z.; Flint, M.M. Do all roads lead to Rome? A comparison of knowledge-based, data-driven, and physics-based surrogate models for performance-based early design. *Eng. Struct.* **2023**, *286*, 116098. [CrossRef]
15. Yang, J.-X.; Zhou, Y.-X.; Dai, S.-H. Intelligent Ontology Model of Bridge Structure Based on Semantic Ontology. *J. Civ. Eng. Manag.* **2020**, *37*, 26–33.
16. Yang, X.-X.; Yang, J.-X.; Li, R.; Luo, M.-T.; Jiang, S.-X.; Wang, G.-P.; Yang, Y.-F. Knowledge graph construction and knowledge question answering method for bridge inspection domain. *J. Comput. Appl.* **2022**, *42*, 28–36.
17. Zhong, M.-S.; Wu, J.-H.; Luo, W.; Wu, S.-X. The BiLSTM-Att-BCRF Model for Low Resource Named Entity Recognition. *J. Jiangxi Norm. Univ. (Nat. Sci. Ed.)* **2022**, *46*, 460–467.
18. Zhu, Y.-W. Study on Evaluation System of Green Low-Carbon Bridges. Master's Thesis, Beijing Jiaotong University, Beijing, China, 2018.
19. Sun, X.-Y.; Dong, W.-W.; Wang, H.-L.; Wang, J. Comprehensive Fussy Assessment of Bridge Life-Cycle Carbon Intensity Index. *J. Basic Sci. Eng. Sci.* **2013**, *21*, 735–747.
20. Zhang, Z.-H.; Tan, R.-P.; Fang, M. Establishment and analysis of carbon emissions model of T-beam bridge during construction. *J. Chang. Univ. Sci. Technol. (Nat. Sci.)* **2018**, *15*, 71–78.
21. Lei, J.-H.; He, X.-H. Green construction technology of a deck-arch railway bridge with concrete-filled steel-tube ribs in canyon area. *J. Railw. Sci. Eng.* **2020**, *17*, 3104–3110.
22. Wang, C.-Y.; Jiang, Z.-H.; Ji, Y.-J.; Wang, F.-H.; Huang, Y.-W.; Xue, M. A Novel Automatic Construction Approach for Ship Outfitting Design Experiential Knowledge Graph. *Mech. Des. Res.* **2021**, *37*, 163–169+181.
23. Li, M.-M.; Chen, W.-G.; Li, L. Research on calculation and influencing factors of carbon emission during the materialization phase of prefabricated buildings. *J. Saf. Environ.* **2023**, 1–10. [CrossRef]
24. Ju, Y.; Chen, Y. Carbon emission calculation in the operation phase of buildings—A study on emission factor method based on carbon emission factors. *Sichuan Build. Sci.* **2015**, *41*, 5.
25. Wang, R.-W.; Yuan, Y.; Yuan, X.-P. Study on the Construction of Chinese Knowledge Graph Based on Deep Learning and Graph Database. *Libr. Inf.* **2016**, *167*, 110–117.
26. Xie, T.; Yang, J.-A.; Liu, H. Chinese Entity Recognition Based on BERT-BiLSTM-CRF Model. *Comput. Syst. Appl.* **2020**, *29*, 48–55.
27. Zeng, D.-J.; Liu, K.; Chen, Y.-B.; Zhao, J. Distant Supervision for Relation Extraction via Piecewise Convolutional Neural Networks. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, Lisbon, Portugal, 17–21 September 2015.
28. Liu, X.-K. The Intelligent Question and Answer System for Legal Aid Comprehensive Service Management Based on Knowledge Graph. Master's Thesis, North University of China, Taiyuan, China, 2022.
29. Chen, X.; Zhang, N.-Y.; Li, L.; Xie, X.; Deng, S.-M.; Tan, C.-Q.; Huang, F.; Si, L.; Chen, H.-J. LightNER: A Lightweight Generative Framework with Prompt-guided Attention for Low-resource NER. *arXiv* **2021**, arXiv:2109.00720.
30. Sun, L.-H. Research on Entity Relationship Extraction Algorithm Based on Cross-Language Transfer Learning. Master's Thesis, University of Science and Technology of China, Hefei, China, 2020.
31. Ma, X.-Q.; Guo, X.-H.; Xue, Y.-F.; Yang, L.; Chen, Y.-Z. Data enhancement techniques for named entity recognition. *J. East China Norm. Univ. (Nat. Sci.)* **2021**, *219*, 14–23.
32. Du, X.-M.; Yuan, Q.-B.; Yang, F.; Yao, Y.; Jiang, X. Construction of Named Entity Recognition Corpus in Field of Military Command and Control Support. *Comput. Sci.* **2022**, *49*, 133–139.
33. Jie, Z.-M.; Xie, P.-J.; Lu, W.; Ding, R.-X.; Li, L.-L. Better Modeling of Incomplete Annotations for Named Entity Recognition. In Proceedings of the 2019 Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL), Minneapolis, MN, USA, 2–7 June 2019.
34. Wu, J.; Wu, C.-H.; Li, Y.; Deng, S.-G. Web Service Discovery Based on Ontology and Similarity of Words. *Chin. J. Comput.* **2005**, *4*, 595–602.
35. Tian, X.; Zheng, J.; Zhang, Z.-P. Jaccard Text Similarity Algorithm Based on Word Embedding. *Comput. Sci.* **2018**, *45*, 186–189.
36. Hancock, J.M. *Jaccard Distance (Jaccard Index, Jaccard Similarity Coefficient)*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2004.
37. Li, Z.-X. Research on Food Safety Case Retrieval Method Based on Knowledge Graph. Master's Thesis, Tianjin University of Science and Technology, Tianjin, China, 2020.
38. Leontief, W. Environmental Repercussions and the Economic Structure: An Input-Output Approach. *Rev. Econ. Stat.* **1970**, *52*, 262–271. [CrossRef]
39. *ISO 14040*; Environmental Management-Life Cycle Assessment-Principles and Framework. International Organization for Standardization: Geneva, Switzerland, 2006.
40. *ISO 14044*; Environmental Management-Life Cycle Assessment-Requirements and Guidelines. International Organization for Standardization: Geneva, Switzerland, 2006.

41. *ISO 14064*; Greenhouse Gases—Part 1: Specification with Guidance at the Organization Level for Quantification and Reporting of Greenhouse Gas Emissions and Removals. International Organization for Standardization: Geneva, Switzerland, 2006.
42. *ISO 14065*; Greenhouse Gases—Requirements for Greenhouse Gas Validation and Verification Bodies for Use in Accreditation or Other Forms of Recognition. International Organization for Standardization: Geneva, Switzerland, 2007.