Machine Learning Informed Knowledge Driven Framework supporting Holistic Bridge Maintenance

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Abstract. Bridge maintenance is a complex task, which demands a wide spectrum of factors to achieve multi-objectives, multi-criteria optimum decisions. Physics-informed analysis can simulate complex and closely coupled problems, e.g., bridge structural analysis. However, it cannot account for some loosely coupled discrete factors, which complementarily could be addressed by ontological based semantic inference. This paper presents an overarching machine learning (ML) informed knowledge driven framework, which can enhance existing and static knowledge base via dynamically linking to real-time ML information for bridge structural safety as the governing consideration, to make accurate and holistic maintenance decisions. The framework includes semantic modelling, ML based numerical modelling and the Web OWL based reasoning mechanism for integration. The approach could contribute to some fundamental mindset changes towards maintenance decision making.

Keywords. Bridge maintenance; Knowledge engineering; Ontology; Machine Learning

1. Introduction

Bridges are a vital part of the architecture, engineering, and construction (AEC) industry, and effective maintenance is essential for ensuring good condition of their structures (Wu *et al.*, 2021a). Embracing advanced information and communications technologies, bridge maintenance tasks are becoming more interdisciplinary, interactive, distributed, knowledge intensive, and data-driven, resulting in an extremely complex process. Proactive, holistic and real-time approaches are required to comprehend the complexity of bridge maintenance scenarios (Jiang *et al.*, 2023).

Semantic Web Technologies (SWT), such as Resource Description Framework (RDF) and Web Ontology Language (OWL), are becoming popular as technological solutions to facilitate holistic decision-making. OWL is a semantic language for developing and sharing ontologies on the World Wide Web. It adds rich semantic expressions to ontologies by building on the RDF representation schema. The core ontologies are knowledge representations of a domain that contain explicit description of concepts, attributes or features of those concepts, and logical restrictions on them. The objective of an ontology is to represent knowledge in a specific domain in a both human and machine-readable format. Distinct from analytics and algorithms, there are several advantages of ontology, including: facilitating knowledge sharing and reuse, supporting interoperability, enabling automated inference, improving information retrieval, and enhancing consistency and accuracy (Hou, Li and Rezgui, 2015; Wu et al., 2021b).

In line with these strengths, numerous ontologies have been developed to facilitate data integration, natural language processing, and information extraction in the AEC domain. Specific to the bridge maintenance sector, existing ontologies are good at integrating static information from industry manuals and norms. Li et al. (2021) presented a bridge structure and health monitoring ontology to achieve fine-grained modeling and enable domain knowledge discovery. Ren et al. (2019) grouped semantically related bridge components, and then embedded rules to achieve automatic condition evaluation related to bridge maintenance operations. However, despite the impact that SWT has had on bridge maintenance projects, the ability of semantic reasoning processes to handle complex numerical calculations is severely lacking. In a decision-making scenario where structural safety as the governing consideration, bridge maintenance needs to consider results of extremely complex mathematical operations. The ability of traditional ontologies in bridge maintenance domain need to be enhanced.

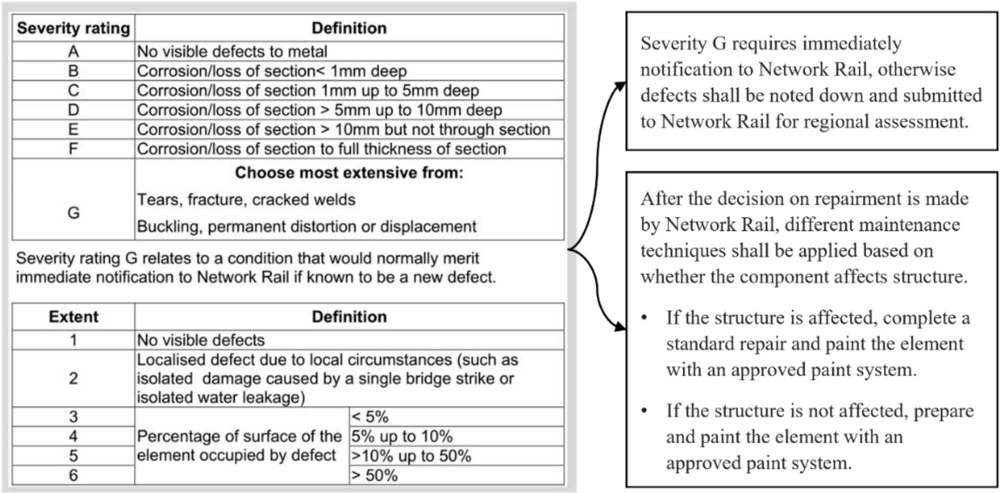
With the rapid popularization of artificial intelligence, the utilization of machine learning (ML) methods for obtaining the structural safety performance of bridges has attracted great interest from researchers. For example, Jaafaru and Agbelie (2022) used ML methods to predict future bridge condition state with the ultimate goal of improving bridge maintenance project productivity, reducing downtime, and improving bridge inventory condition. Liu et al. (Liu *et al.*, 2022) developed an ANN-based method for rapid seismic fragility assessment of regular bridges, and their work indicated that the method is an effective alternative for seismic assessment of bridges with significantly reduced computation time. However, numerical analysis cannot account for loosely coupled discrete factors in bridge maintenance, e.g. maintenance planning and scheduling. Purely numerical methods have limited capabilities to handle such bridge maintenance tasks.

In summary, this paper presents an overarching machine learning informed knowledge driven framework, aiming at orchestrating the aforementioned decision making instruments together. The framework integrates ML-based methods into semantic inference processes, allowing knowledge-driven methods to handle complex mathematical operations in real-time and make holistic decisions. Additionally, an ML-based surrogate model accurately judges the status of an in-service bridge, making it more reasonable to infer maintenance decisions considering the current state of the structure. The main contents include:

- Creating a comprehensive semantic model called Bridge Maintenance Ontology (bmo) to model the TBox (T stands for Terminological) by following standard procedures and the semantic format of OWL.
- Training an ML-based surrogate model to supply real-time ABox (A stands for Assertional) of the bmo.
- Creating a set of semantic rules using the formal logics of SWRL (Semantic Web Rule Language) to enable ML-informed decision-making.
- Introducing an example of a real bridge project in the UK to demonstrate the novel decision-making scenarios.

2. Motivating scenario and overarching framework

As noted by Uschold and Gruninger (1996), the development of ontologies can be motivated by practical use cases. In this context, motivating scenarios are helpful in defining the scope of the ontology and determining the meaning and relationships of important classes. In this research, the motivating scenario is based on a real railway bridge, River Neath Swing Bridge which is currently undergoing fundamental maintenance due to significant corrosion to structural elements. Maintenance solutions are highly related to visual defects of structures which is used to assess the condition of bridges. **Figure1** shows the method defined in Network Rail Standard NR/L3/CIV/006 for determining the defect severity and extent rating of metallic elements of bridges. Although it can roughly quantitatively display defects rating, it cannot accurately determine whether it has a substantial impact on the structural safety performance. Maintenance decisions are largely based on the subjective influence of engineers.



Severity rating	Definition
A	No visible defects to metal
B	Corrosion/loss of section< 1mm deep
C	Corrosion/loss of section 1mm up to 5mm deep
D	Corrosion/loss of section > 5mm up to 10mm deep
E	Corrosion/loss of section > 10mm but not through section
F	Corrosion/loss of section to full thickness of section
G	**Choose most extensive from:** Tears, fracture, cracked welds; Buckling, permanent distortion or displacement

Severity rating G relates to a condition that would normally merit immediate notification to Network Rail if known to be a new defect.

Extent	Definition	
1	No visible defects	
2	Localised defect due to local circumstances (such as isolated damage caused by a single bridge strike or isolated water leakage)	
3	Percentage of surface of the element occupied by defect	< 5%
4		5% up to 10%
5		>10% up to 50%
6		> 50%

Figure 1: Severity and extent ratings for metallic elements of bridges

Therefore, this research leverages ML methods to provide accurate judgements on the bridge performance to assist engineers making holistic maintenance decisions with consideration of safety, cost and maintenance planning. **Figure 2** depicts the overarching ML-informed knowledge driven framework for this maintenance scenario, including ontology modelling, ML-based modelling and the Web OWL based reasoning mechanism for integration. The workflow is as follows: firstly, knowledge engineers translate static knowledge defined in a series of Network Rail Standards and motivating scenarios into ontology and SWRL rules to form a bridge maintenance knowledge base. Meanwhile, structural engineers develop ML model based on finite element model of bridges to timely predict structural safety performance. These predicted results are stored in the knowledgebase in a semantic format. Then, engine interfaces execute tasks and generate facts. Finally, users obtain useful information by setting multiple constraints with consideration safety, cost and maintenance planning to make decisions.

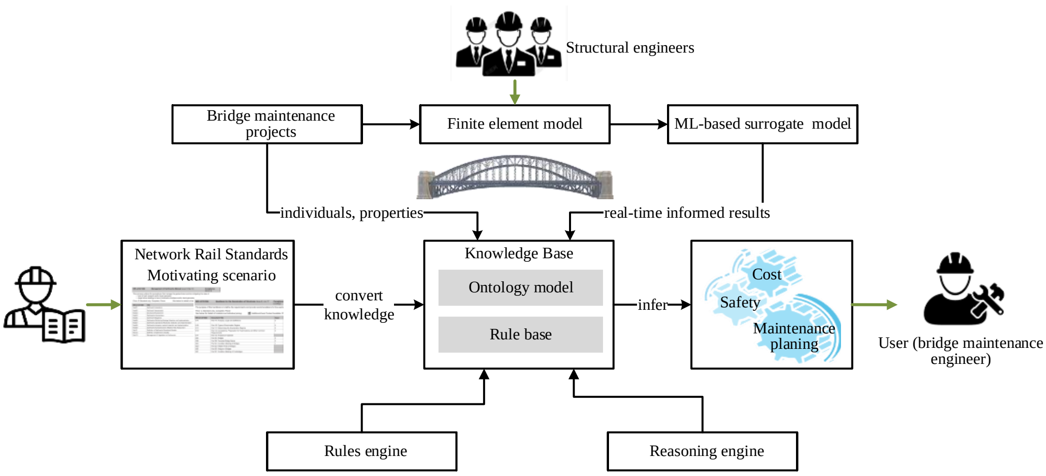


Figure 2: The overarching ML-informed knowledge driven decision making framework

The framework integrates static knowledge defined in standards along with dynamic and informed information from ML analysis to automate semantic inference. The market survey has shown that there are more than 17,500 bridges of the UK rail network constructed 100 years ago which are endure the same problems with the case bridge. Such a method can be applied to any of those bridge to provide accurate judgements on the bridge performance to assist engineers making holistic maintenance decisions.

3. Development of ML model

The structural analysis and the corresponding ML surrogate model are built based on one of the main girders which is the key structural component. The ML surrogate model is built on an in-put-out-put pattern. There will be two parameters considered as in-put, which are area of the corrosion and depth. While the output is the maximum deflections and the maximum Von Mises strain in the girder considering structural criterion and strength criterion, respectively. The selections of input parameters are meant to be consistent with the bridge maintenance standard NR/L3/CIV/006 (Part 2C: Condition marking of Bridges). As the locations of corrosions are not specified in the standard, all corrosions are concentrated in the centre of the bridge component, which presumably causes the most deformation and stress.

Based on the manual, rating of corrosions for metallic elements are marked from A-G as severity and 1-6 as extend. The severity ratings are marked based on the depth of the corrosion, e.g. if the corrosion is less than 1mm deep, it will mark as B. Whilst the extend ratings are marked based on the percentage of the corroded area over the whole surface of the element. It is worth noting that, the severity rating of A, F and G indicates no visible defects to metal and tear, fracture, cracked welds, etc., which causes the failure of the structure and require immediate attention, respectively, are not considered in the modelling. Whilst rating for extent has mark of 1 and 2 representing no visible defects and localised defect, which will not affect the performance of the structure. Such rating will not be included in the structural analysis as well. The range for severity rating is therefore from 0 mm to 10 mm covering rating from B-E. Similarly, the rating for extent is ranged from 0% to 100% covering rating from 3-6.

The loading of the structure is guided by the standard NR/GN/CIV/025. As a simply supported span, the loading is advised to follow the loading case of Route Availability (RA) 10 which is applied on each track with an equivalent uniformly distributed loading (EUDL) and end shear of 20 units of RA1. The dynamic loading is also considered with a factor of (φ_1 + φ_{11}) of the static loads as the track is designed to be less than 100 mph according to the standard, where φ_1 and φ_{11} can be calculated using following equations.

$$\varphi_1 = \frac{k}{1 - k + k^4}$$

Where

$$k = \frac{v}{4.47 L_\phi n_0}$$

Where v is the permissible speed on the bridge. L_ϕ is the determinant length of centre to centre of supports in metres as tested element is a through bridge main member. n_0 is the fundamental natural frequency of the structure tested 16.8Hz using an vibration camera and analysed using Fast Fourier Transform.

And for φ_1

$$\varphi_{11} = \alpha[56e^{-\left(\frac{L_\phi}{10}\right)^2} + 50(\frac{Ln_0}{80} - 1)e^{-\left(\frac{L_\phi}{10}\right)^2}]$$

Where $\alpha = 0.0002v$

For the end shear a factor of 2/3 ($\varphi_1 + \varphi_{11}$) is applied. As such load is transferred to the tested member through stiffeners connected to the main girder. To assure the data domain is mapping randomly and seamlessly, a Markov Chain Monte Carlo (MCMC) is applied to generate the samples which is used as input for both FE and ML. The FE model is built using a combination of 2D triangles and rectangular shell element (S3R and S4R) with five integration points with average edge size of 150 mm. 1120 samples are generated and trained into a surrogate model.

The ML model is trained using several machine learning algorithms, i.e. Random Forest (RF), Artificial Neural Network (ANN), and Gaussian Process Regression (GPR). To avoid overfitting and retain the accuracy of the model, 10-fold with 10 % test data set is applied during training. The models are then evaluated using R^2 and RMSE. The results are shown in **Figure 3**. It can be seen that the GPR has the best prediction accuracy in terms of the R2 and RMSE comparing with RF and ANN.

The R2, the coefficient of determination, reaches 99.8% in GPR indicating the predictions from model are almost the same as the FEA solutions. For most of the ML algorithms, such a high value might indicate the overfitting problem. However, the GPR, as a non-parametric ML model, is not hunted by such issue. While the RMSE, on the other hand, is the Root Mean Square Error, compared with FEA, providing another evaluations for the model. As the standard derivation of the test set are almost 1000, the RMSE with 4.692 for GPR is considered as very high accuracy. The GPR model can, therefore, provide reliable predictions in such a scenario.

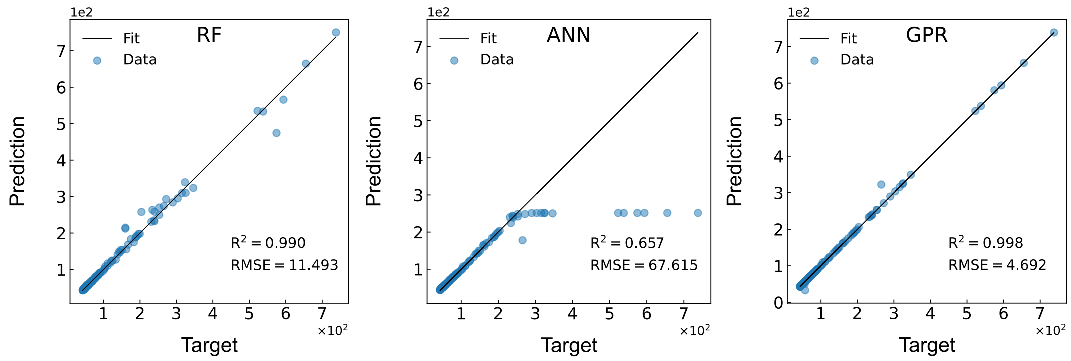


Figure3: R2 and RMSE for RF, ANN and GPR

4. Development of knowledge base

4.1 Bridge maintenance ontology

The research approach of ontology development includes ontology specification, knowledge acquisition, conceptualization, implementation, and evaluation (France-Mensah and O'Brien, 2019). The methodology used is a combination of two approaches: the "methontology" approach (Fernández-López *et al.*, 1997) and the "Uschold and Gruninger" ontology building approach (Uschold and Gruninger, 1996). Together, these two approaches create a comprehensive methodology for building ontologies. It is first important to define the scope and purpose of the ontology. The application domain of the bmo is the field of bridge maintenance. The bmo is designed to connect ML-informed results to provide accurate judgments of bridge performance, and assist engineers in making holistic maintenance decisions with consideration of safety, cost, and maintenance planning. Following this, knowledge capture and taxonomy of relevant terms were conducted. To avoid ambiguity and facilitate the later expansion of the ontology, standards NR/L3/CIV/006, NR/L3/CIV/020, and NR/GN/CIV/025 were analysed to collect unified terminology, including defining the major elements and minor elements, and scoring the condition of elements in quantitative terms, such as the severity and extent of visible defects. Beyond this stage, the ontology was formally coded using OWL in a semantic, computational logic-based format. The coded ontology then underwent internal logical checks and was subsequently implemented in a case study.

A UML diagram-based version of the highest level terms in bmo is illustrated in **Figure 4**, including 18 core classes, 23 object properties, and 20 key data properties. Classes are used to organize and classify knowledge in a systematic way. They are further subdivided into subclasses, allowing for a hierarchical organization of knowledge within the ontology. For example, according to the principle of whole to part, the class ‘Element’ is divided into classes ‘MajorElement’ and ‘MinorElement’. Properties are used to describe the relationships between classes and the attributes of the members of those classes. Properties link them together to form RDF triples. Depending on the specific requirements of the bmo, some properties with characteristic setting, quantifier restrictions, cardinality restriction, domain and range restriction are created to describe characteristics of various individuals in both a quantitative and qualitative way.

For example,

- characteristic settings: cooperateWith is Symmetric
- existential restrictions: hasElement some Element
- universal restrictions: hasElement only (Element or MiscellaneousItem)
- qualified cardinality restrictions: spanNumder exactly 1 xsd:int
- domain restrictions: purpose domain Standard
- range restrictions: address range xsd:string

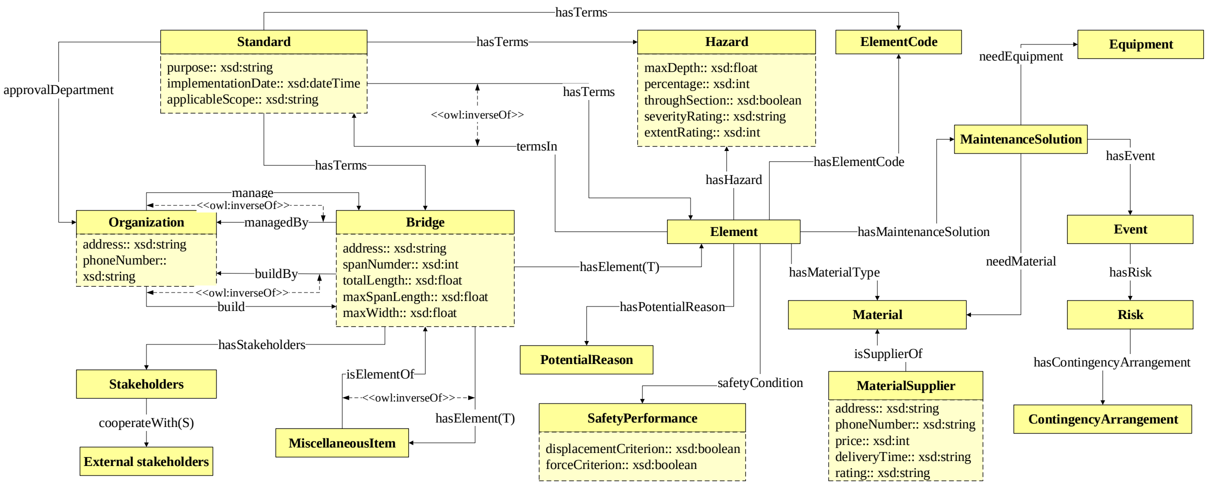


Figure 4: The high-level overview of the ontology

The above information is formally represented using OWL formal language, and a URL (Uniform Resource Locator) is added in the form: https://w3id.org/bmo. To this end, the bmo can already run built-in reasoners, such as Pallet, to start logical inference. As depicted in **Figure 5**, some individuals and their relationships are added (shown in blue). However, some instances do not have an exact correspondence with the ontology. In this example, an individual ‘River Neath Swing Bridge’ is subdivided into major elements, e.g. deck. An main girder ‘longitudinalMainGirder(exposed)1’ is further assigned to the deck1. Then some data property ‘spanNumber’ and object properties ‘hasStakeholders’, ‘cooperateWith’ are added. Based on previously defined semantics, when synchronizing the reasoner, implicit knowledge will be obtained in an explicit way. Inconsistencies are alerted and highlighted in red, while consistent results are highlighted in yellow. Consistent information can be continuously added to the ontology, further enriching it.

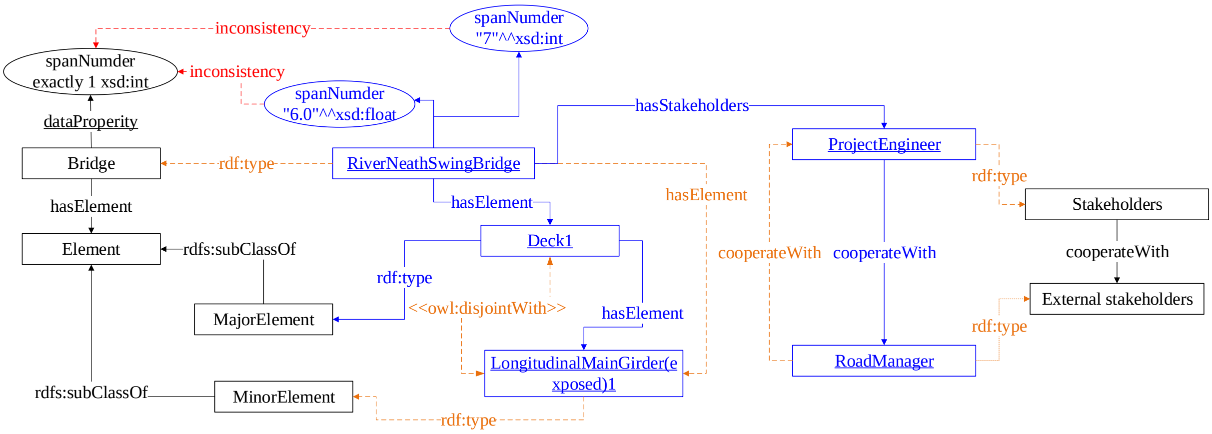


Figure 5: Examples of semantic reasoning

4.2 Reasoning rules

Besides making implicit information explicit, more advanced deductive reasoning capabilities are required to meet demands of the maintenance scenario. On the basis of the defined ontology, a total of 38 SWRL rules are created to generate new knowledge through the codification and analysis of “if-then-else” conditions to calculate new values for properties. **Table 1** lists some SWRL rules for infer maintenance solutions based on the severity rating and safety condition of elements.

Table 1: Examples of SWRL rules for semantic reasoning.

Rule 1	Determining the severity rating of corrosion.
	If the corrosion is 1mm up to 5mm deep, the severity rating of corrosion is C. Corrosion(?C)^maxDepth(?C,?Cd)^swrlb:greaterThanOrEqual(?Cd,1)^swrlb:lessThanOrEqual(?Cd,5)^throughSection(?C,false) -> severityRating(?C,"C")
Rule 2	Inferring the severity rating of elements.
	If there are corrosions to metal, the severity rating is inferred. Element(?E)^hasMaterialType(?E,?Em)^Metal(?Em)^hasHazard(?E,?Er)^Corrosion(?Er)^severityRating(?Er,?Ers) -> severityRating(?E,?Ers)
Rule 3	Inferring the safety condition of elements based on machine learning predictions.
	The safety condition is TRUE only if both the displacement and stress criteria are met. Otherwise the safety condition is FSLAE. Element(?E)^displacementCriterion(?E,true)^VonMisesStressCriterion(?E,true)-> safetyCondition(?E,true)
Rule 4	Inferring maintenance solutions based on the severity rating and safety condition of elements.
Rule 4-1	If structure is not affected, preventive maintenance is needed, and the element need to be painted with an approved paint system. Element(?E)^safetyCondition(?E,true)^severityRating1(?E,?Es)^swrlb:equal(?Es,"C") -> hasMaintenanceSolution(?E,PreventiveMaintenance)^maintenancePlaning(?E,"structure is not affected, the element need to be painted with an protective coating systems.")

Rule 4-2	Severity G requires immediate notification to Network Rail. Element(?E)^ severityRating(?E,?Es)^swrlb:equal(?Es,"G") -> hasMaintenanceSolution(?E,EmergencyMaintenance)^maintenancePlaning(?E,"Severity G requires immediate notification to Network Rail, otherwise defects shall be noted down and submitted to Network Rail for regional assessment.")

5. Case study implementation

In this research, the motivating scenario is based on a real railway bridge, the River Neath Swing Bridge, which requires maintenance decisions due to significant corrosion to structural elements. Two applications are implemented to verify the competency of the proposed knowledge-driven framework.

- Application 1: ML-based informed maintenance decisions inference.

As shown in **Figure 6**, the metal individual ‘LongitudinalMainGirder(exposed)1’ has corrosion defects. The depth and percentage of corrosion is 3 mm and 9%, respectively. When synchronizing the reasoner, all relevant attributes are highlighted in yellow. On the one hand, implicit logical attributes are made explicit. ‘LongitudinalMainGirder(exposed)1’ is a minor element assigned to the deck1 of the River Neath Swing Bridge. On the other hand, new properties values are inferred based on the visual severity and ML-based predictions of hazards. Although the structure is not severely affected by corrosion, preventive maintenance needs to be implemented, and the element need to be painted with an approved paint system. Moreover, potential reasons are inferred, including improper construction, painting quality, acidic environment, and poor drainage condition.

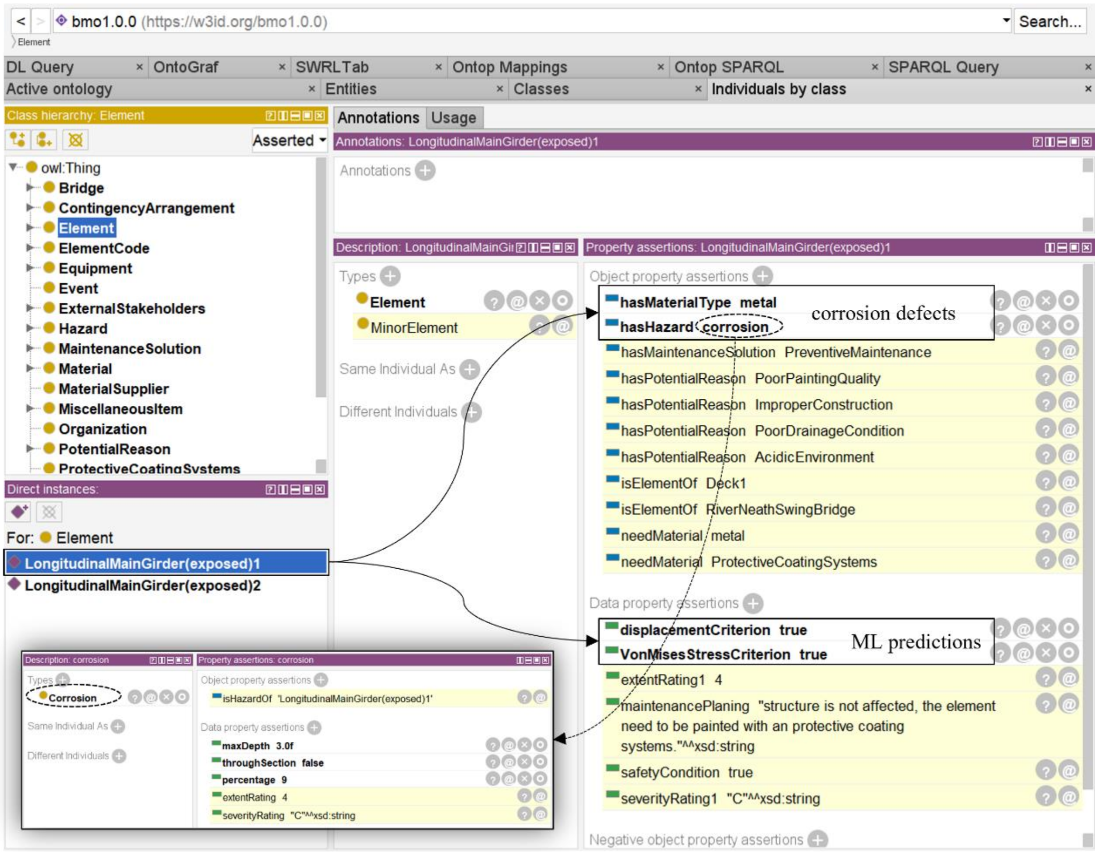


Figure 6: ML-based informed maintenance decisions inference

- Application 2: Using SPARQL to query solutions with multiple constraints.

  In this part, SPARQL (SPARQL Protocol and RDF Query Language) is used to select information stored in RDF format. As shown in **Figure 7**, SPARQL queries are composed of various elements, including prefixes, variables, and triple patterns. When the query is executed, the metal's supplier with consideration of rating, price and delivery time are selected and listed. All information is used to assist engineers making holistic maintenance decisions.

SPARQL query:

```
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX bmo: <https://w3id.org/bmo#>
SELECT ?companyName ?information ?rating ?address ?phoneNumber ?price ?deliveryTime
WHERE {
        ?companyName    rdf:type    bmo:MaterialSupplier;
                        bmo:isSupplierOf bmo:metal;
                        rdfs:comment ?information;
                        bmo:rating ?rating;
                        bmo:address ?address;
                        bmo:phoneNumber ?phoneNumber;
                        bmo:price ?price;
                        bmo:deliveryTime ?deliveryTime;
        FILTER (?rating = "Very good" && ?price < 3000 && ?deliveryTime < "8days")
}
```

companyName	information	rating	address	phoneNumber	price	deliveryTime
CUMIC	"中联物产致力于为全球	"Very good"^^<http://ww	"CUMIC Shanghai (HQ)	"+86 (21) 56118383"	"1200"^^<http://www.w3.	"7days"
STEMCOR	"STEMCOR is a leading	"Very good"^^<http://ww	"Stemcor Global Holding	"+44 (0)20 7775 3600"^	"2500"^^<http://www.w3.	"5days"

Figure 7: Using SPARQL to query solutions with multiple constraints

6. Conclusion

This research leverages both ML methods and semantic web technologies to provide accurate judgments on the performance of bridges, helping engineers make holistic maintenance decisions that consider safety, cost, and maintenance planning. By predicting the safety performance of bridges using an ML-based surrogate model, computationally expensive and time-consuming analysis during the FE analysis process can be avoided. ML-based methods are integrated into semantic inference processes, traditional ontologies can handle complex mathematical operations, and it is more reasonable to infer maintenance decisions with considering the current state of the structure. A motivating scenario based on a real bridge project in the UK is introduced to demonstrate the competency of the proposed knowledge-driven framework. The approach could contribute to fundamental mindset changes towards systematic and holistic decision-making.

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