A knowledge-based Approach for the Assessment of Damages to Constructions

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Abstract

To assess detected anomalies as well as assume undetected damages of an existing construction, a knowledge-based approach for damage evaluation is presented, whereby data from multiple web ontologies are linked via Linksets that are stored in an Information Container for Data Delivery (ICDD)[1]. In the ICDD, an ontological model that represents the assessed construction is linked with a damage ontology, which is necessary to identify various damage types that could affect the construction. Additionally, the web ontology representing the construction is linked with a Building Information Model (BIM) in the IFC-Format to enable access to the geometrical data of the components. Similarly, the damage objects are linked with either recorded geometry data or a manually created geometry model. Predefined rules are applied on the assertion components of the web ontology for reasoning damage types of each detected anomaly and damage assessment. Furthermore, the existence of undetected damages can be reasoned based on information about the construction, environment and previously classified damages. The developed web ontologies in this research use the principles of Linked Data and are serialized in the data format OWL. This enables the utilization of already existing Linked Data ontologies as well as supporting the implementation and development of future ones.

Keywords: Damage Classification, Building Information Modeling, Construction Assessment, Ontologies, Linked Data

1. Introduction

Technological Advancements in the field of anomaly detection in structures enable the utilization of tools and systems that can process an automatic identification and localization of defects and structural damages, which physically harm existing constructions so that their structural capacity, durability or usefulness is impaired. However, the classification of these anomalies and the reasoning of undetected damages (e.g. overseen or unreachable ones) is performed manually by an expert. Additionally, after the classification process is finished, it is necessary that the expert evaluates the damage by considering properties, which have an influence on the maintenance of the construction, e.g. impacts on the structural capacity, durability or traffic safety. For this purpose, standards are used in certain countries, e.g. DIN 1076 in Germany (BVBS, 2007) which use a grading system to assess the damages and determine the overall condition of the construction. However, in using these standards, the damage assessment is often simplified to assigning a generalized grade or limited number of condition indexes. A detailed classification and identification of the damage cause is often only recorded in non-machine interpretable or even non-digital formats, e.g. handwritten inspection protocols or images, thus further processing and managing of these data, especially in later lifecycle stages of the construction is more difficult. Furthermore, for analyzing more accurately the structural capacity of the construction it is necessary to model the system in a damaged state according to principles in structural analysis such as the smeared crack approach ((Bažant & Oh, 1983). However, the exact mechanical

[1] https://www.iso.org/standard/74389.html

parameters, which characterize the damage are not derivable. For this purpose, a simulation-based system identification is required, where additional measurement data are utilized, which reflect the behavior of the construction under known load (Luu, Hamdan, Polter, Scherer, & Mansperger, 2018). Thereby, the damage parameters need to be variated in order to identify a system that fits best to the monitored structural behavior. Thus, using this approach, it would be possible to estimate more precisely suitable refurbishment methods for existing constructions. However, manual definition of damage parameters would be very time consuming and not feasible in an appropriate time without automation. Therefore, in this research a computer-based approach for damage classification and assessment has been developed which utilizes Semantic Web technologies for inferring properties from detected anomalies. Anomaly data, which can be either created manually or by utilizing appropriate tools are used for creating a web ontology using the Web Ontology Language (OWL)[2] as data format. Thus, OWL supports the application of inference mechanisms based on description logic through reasoning engines as well as modelling the information in a graph which uses Unique Resource Identifiers (URI) for identifying each dataset. By using rule languages such as SWRL, DROOLS or SHACL, classification and evaluation rules are defined which are then applied on the anomaly data. Consequently, a presumption of undetected damages as well as identifying the reduced mechanical parameters is processed by analyzing the information from semantic reasoning in combination with a numerical structural analysis. In this context, the workflow can be utilized as part of the BIMification process (Scherer & Katranuschkov, 2018), where an in depth survey of damages is an important step. In this paper, the concept of the approach is explained on a detailed workflow. In addition, the utilized web ontologies and linked models are described. Furthermore, the concept of applying rules for classification, evaluation and assumption is presented, using specific examples from maintenance of reinforced concrete bridges.

2. Related Work

Systems for the automated classification of defects have already been developed in other fields, such as (Patent No. US5544256A, 1996), where a fuzzy logic inference engine is utilized to classify object defects in various products. Concerning constructions in civil engineering, various approaches regarding damage classification and assessment focus on utilizing machine learning. Thereby, the Nanjing HuoYang Hou Mdt InfoTech Ltd. developed a system that detects various damages in metro tunnels and analyze them by processing automatic machine recognition and quantitative damage analysis (Huang, Fu, Chen, Zhang, & Huang, 2018). Another notable approach uses support vector machines for the recognition and evaluation of bridge cracks (Li, Zhao, Du, Ru, & Zhang, 2017). All these approaches have in common that a large amount of training data is needed as a prerequisite to get accurate results by using machine-learning methods. Therefore, a method for classifying building defects with case-based reasoning has been developed by (Xu, Li, Li, & Li, 2018), which requires a comparatively smaller number of reference subjects.. Other approaches have also been developed using Semantic Web technologies. In this regard, (Lee, Chi, Wang, Wang, & Park, 2016) proposed an ontology-based system for querying specific defect cases based on construction conditions, which were derived from a BIM model. Furthermore, an ontological model has been developed in the research project MONDIS, which defines damage causations and corresponding damage properties for historical constructions and thus can also be used for damage classification and assessment (Cacciotti, Blaško, & Valach, 2015). An approach which enhances the reasoning process with SWRL rules has been elaborated by (Ren, Ding, & Li, 2019). Thereby, the rules are used for applying condition indexes to detected cracks and therefore process a damage assessment.

Despite these various developments in the field of machine-based damage classification and evaluation, no approach exists at the time of this publication, which assumes undetected or hidden damages in existing constructions.

[2] https://www.w3.org/OWL/

3. Workflow of Damage Assessment

The objective of the knowledge-based damage assessment is the creation of a damage map that includes both the previously detected damages and undetected suspected damages, which have a negative impact on the structural capacity of the construction. The workflow in Figure 1 depicts how this damage map is created and serialized as an ontological model in OWL.

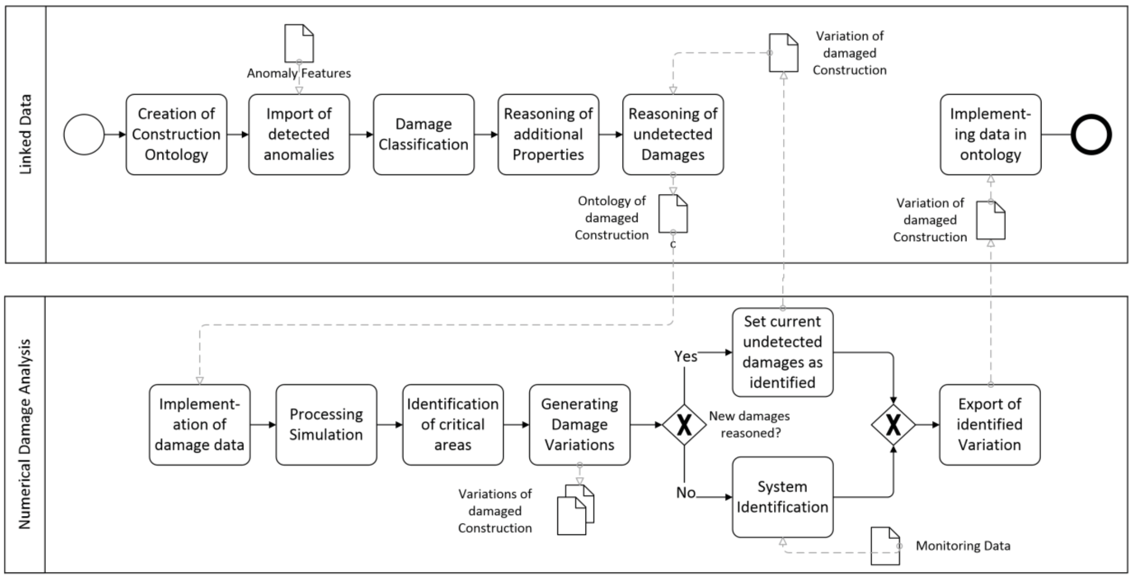

Figure 1 Workflow of the knowledge-based Damage Assessment

In addition to semantic reasoning, a numerical analysis is utilized to reduce the range of possible locations for assumed damages in the resulting damage map. However, besides the numerical approach, other ways of identifying an assumed damage are also possible, e.g. through an additional inspection with detection tools or material tests.

Before a knowledge-based damage assessment can be processed, an ontological model representing the affected construction needs to be created. In this regard, existing construction ontologies such as the Building Topology Ontology (BOT) (Rasmussen, Pauwels, Hviid, & Karlshøj, 2017) can be utilized as a core ontology for defining the topology of the construction and their aggregated elements and zones. Together with domain specific extensions, a data representation of the affected construction can be modeled, which supports knowledge-based operations.

Subsequently, a web ontology is produced based on previously recorded damage data. The damage recording process is not bound to a specific data format. For instance, data from detection tools can be used as well as manually recorded damage descriptions by an inspector. However, it is important that the data is stored in a machine-readable format and that the damage characteristics are filterable for implementation in the web ontology. In this regard, approaches for machine-based damage detection such as by (Morgenthal et al., 2019) are suitable for importing detection data to a web ontology for damage representation, since these data are modelled as feature values, which can be processed immediately. Since images and descriptions made by humans are not machine-readable, a direct input to a web ontology via an optional graphical user interface is recommended for manual damage recording.

When an initial damage representation has been created as web ontology, further reasoning via inference mechanisms and predefined rules can be applied to classify the recorded anomalies. In a similar way additional properties such as mechanical or assessment parameters are derived based on the damage classifications. Additionally, it can be inferred whether undetected structural damages could exist and which potential component types they could affect. However, locations or specific values cannot be derived. Therefore, further numerical data processing is necessary to identify the assumed damages. The information from the construction and damage ontology are used to generate a structural analysis model that can be used to identify critical areas, where a damage occurrence is probable due to overload and could lead to a significant reduction of the structural capacity. Thereby, damages are mapped to the structural analysis model as areas with reduced material parameters using the smeared crack approach (Bažant & Oh, 1983). A mapping of cracks using the discrete crack approach could also be possible, however due to the more complicated modeling and data processing this method has not been investigated in this research. Since it is not sure whether damages occur in the critical areas identified in the simulation process, different variants are created that combine multiple damaged areas with each other as well as variate their related mechanical properties. Thereby, the results from the semantic reasoning in the ontology are considered, to reduce the amount of possible damage variants by a significant amount. The identified damages in each variant could then lead to new assumed damages, by applying assumption rules while considering the previously concluded damages. For this reason, the variants are inferred again in the ontology and evaluated in the numerical simulation in an iterative process until no new damages occur. The resulting variants are then evaluated against monitored data of the construction behavior under the same loads as in the simulation, thus a system identification can be processed and the best fitting variant of the damaged structure is identified (Luu et al., 2018). Since, the process requires a lot of computing performance, the generation of variants and system identification in this method has to be highly automated. This has not yet been tested and validated to its full extend. However, it is possible to realize the proposed method by utilizing new Grid or Cloud technologies. For that purpose a BIMgrid framework was developed by (Polter & Scherer, 2018).

Finally, the best fitting variant of the damaged construction is serialized as resulting damage map in OWL for future damage information management.

4. Structure of the Damaged Construction Ontology

For the mere knowledge processing, only information is necessary that describes the existing construction and the associated damages, which can be stored in one or multiple web ontologies. This information is often present in other models or documents. Within the scope of BIM, the Industry Foundation Classes (IFC) is an established standard for storing construction information and interlinking it with a geometrical representation. Equivalent sets of information between the IFC model and the construction ontology are identified and linked together by using the ICDD. Linking other resources with the ontology, e.g. inspection reports or images is possible and recommended for a comprehensive data management. In a similar way, the damage ontology is linked with a geometrical representation utilizing common formats.

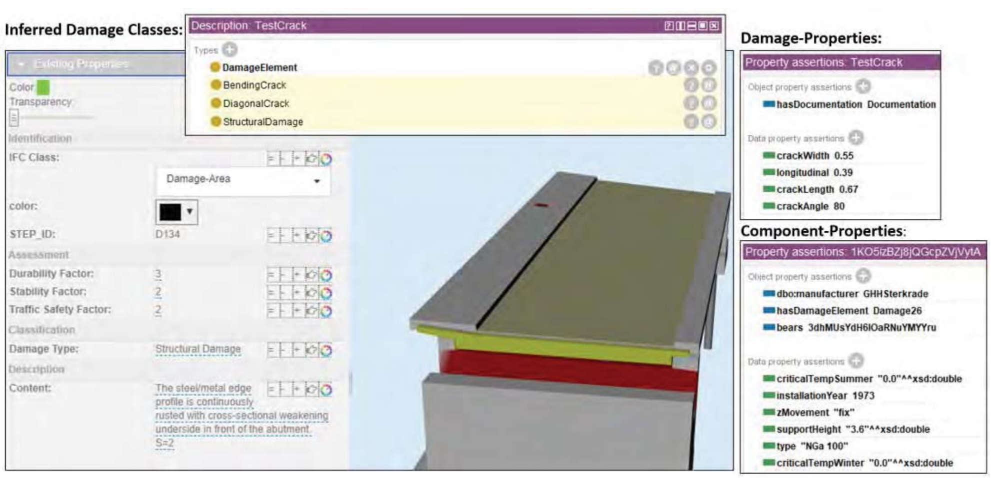

Figure 2 Visualisation of Damaged Construction (ifcwebserver.org) & Ontology Information

4.1 Construction Ontology

The structure of the ontology that represents the existing damaged construction varies and is always strongly dependent on the construction type and the requirements for the specific use cases. The web ontology should consist of metadata about the construction, its history and environmental influences as well as about their aggregated components. Additionally, information about the used building materials is necessary, since the type of damage that could affect a structure is heavily dependent on the used material. Furthermore, structural analysis information about the construction and components is recommended for a more streamlined mapping of the ontology to a FE model or other type of structural analysis model. Consequently, the construction ontology should consist of a topology, classifications for bridges and their aggregated components and material as well as structural analysis information. The IFC model is mainly used for holding the graphical data of each component and the entities are linked with the semantic data from the bridge ontology, so that the resulting ICDD could be graphically as well as semantically processable, provided that appropriate software for this application is developed.

4.2 Damage Ontology

The damage ontology uses terminological components of the Damage Topology Ontology (DOT) (Al-hakam Hamdan, Bonduel, & Scherer, 2019) to define a core ontology for damage representation, which is based upon the Generic Damage Model approach (A Hamdan & Scherer, 2018). Thereby, DOT defines digital *Damage Elements*, which can be aggregated via using a specific object property in a *Damage Area* that represents damages at a lower detail level. Furthermore, *Damage Elements* inside a *Damage Area* can be marked as physically connected objects, either by concatenating them with certain object properties or grouping them by utilizing a specific *Damage Pattern* class.

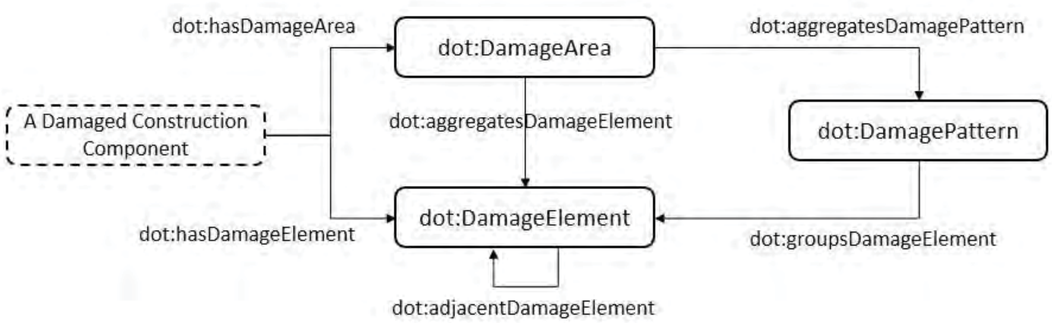

Figure 3 Topological components of DOT (Al-hakam Hamdan et al., 2019)

Besides topological definitions, simple classifications regarding the impact on the structural capacity of a construction for each damage object are supported by differing between structural damages and defects. While structural damages have a negative impact on the structural capacity, this does not apply to defects. However, defects can affect the durability, traffic safety or other factors in a negative way. Additionally, simple descriptions or external documents can be put in relation to the damages in conjunction with additional metadata (e.g. author, date of inspection, etc.). Therefore, DOT can be used as a standalone ontology for storing damage representations and managing them. However, more specific attributes that describe damages of certain types, e.g. the width of a concrete crack, are not covered by DOT. In order to solve this problem, DOT is extended by further terminological components that reflect domain specific knowledge about damage to specific materials or components. Thus, this research the core ontology has been extended with definitions about damages which occur in reinforced concrete as well as about damages that affect bridge components. One feature of these extensions is that they only define new classes for classifying damage in the form of taxonomies, and data properties that characterize these new damage types, thus ideally, no new object properties are added. *Figure 4* shows an example of the taxonomy from the ontology extension for damage classification in reinforced concrete, including the associated data properties.

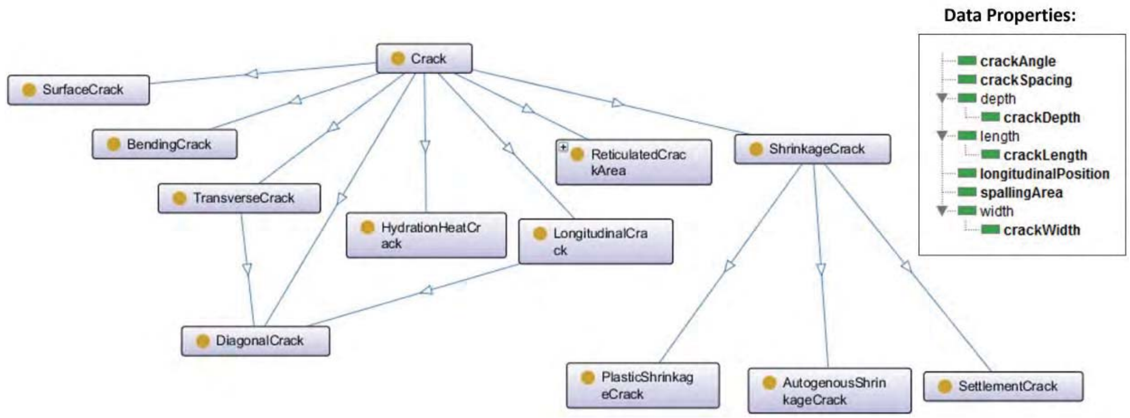

Figure 4 Taxonomy and Data Properties of an ontology extension for damages in concrete.

An exact geometry, as it is used with independent geometry models for visualization, is not defined in the ontology, because the data used for a geometrical representation would be inefficiently stored in an RDF file compared to data formats like Wavefront, Collada or IFC. Furthermore, despite approaches for defining geometry in Linked Data exists, such as by (Pauwels, 2017) or (Shaya, n.d.), no visualization tool exists for processing these data. Because of this, an approach similar to the geometrical representation of the construction ontology is used, whereby a separate geometry model in a data format that is processable by common visualization tools is used and linked with the damage ontology by utilizing the ICDD. Therefore, the URIs of the damage representations from the ontology are linked with the identifiers in the geometrical representation of the damage, thus only geometry formats with referable unique identifiers can be used for this application.

5. Application of Assessment Rules

In this section, rules for classifying and evaluating detected anomalies are described. Additionally, assumption rules are proposed for inferring undetected damages. Since these damages need to be proven as existent either through detection or system identification, they are labeled as uncertain, using the specific class *AssumedDamage*. For better clarification, simple examples are also presented, which refer to the degradation of an existing bridge. All rules are described in first-order logic in this paper.

5.1 Classification Rules

The detected anomalies in the ontology are either declared as a *Damage Element* or *Damage Area* with no further specification. Additionally, quantifications are assigned to each anomaly individual. Therefore, the various evaluation objectives need to be accomplished during the subsequent classification process. Initial classifications can already be made based on individual damage characteristics, which can lead to further inferences. Theoretically, this classification step can be skipped, however it simplifies the definition of resultant rules and enhances their comprehensibility due to the possibility to refer to the reasoned classes instead of certain properties. For instance, recorded cracks can be grouped into longitudinal, transverse or diagonal cracks based on their angle in relation to the affected component (see Equation 1 for example on diagonal crack).

$$\forall d \exists a \exists x \exists y (Crack(d) \land crackAngle(d,a) \land (a > x) \land (a < y) \rightarrow DiagonalCrack(d)) \quad (1)$$

However, the application of such a classification rule needs exact definitions that determine at which value ranges the damage is assigned to the specific class. In Equation 1 no standard defines at which angle a crack can be classified as diagonal crack. In general, this classification is mainly based on human interpretation. Therefore, provisional value ranges (e.g. x = 30; y = 60) can be defined in order to test the developed rules. Furthermore, it could become difficult for humans to classify a damage according to these criteria if multiple damages are physically connected through a pattern and possess different properties, e.g. a crack pattern that starts as a vertical crack and then evolves into a diagonal or transverse crack. Therefore, it is important to subdivide these patterns into single damage elements.

Another fact, which is of interest for the construction maintenance is the causation of the detected damage. Therefore, domain specific rules can be applied, which are mostly based on common expert knowledge. As an example, reasoning the settlement of fresh concrete as a causation for identified cracks is shown in Equation 2.

$$\forall d \exists co \exists cc \exists x \exists y (LongitudinalCrack(d) \wedge \mathrm{hasConcreteCover(co, cc)} \wedge \mathrm{crackDepth(d, x)} \wedge (\mathrm{x < cc}) \wedge \mathrm{crackWidth(d, y)} \wedge (0.5 < \mathrm{y} < 2) \rightarrow SettlementCrack(d)) \quad (2)$$

Based on a previous classification regarding the crack angle, a longitudinal crack is identified. Alternatively, the value range of the measured angle can be asserted, which is more suited towards a machine-based damage detection. In addition, the width and crack are checked that must be in a certain value range, whereby the depth must not exceed the thickness of the concrete cover. If all three criteria are fulfilled the crack can be identified as a crack caused due to concrete settlement. Consequently, a new class is assigned to the damage, which indicates the causation. As an alternative, the causation can be defined via a string-based data property. One important fact that needs to be reasoned is whether an anomaly has an impact on the structural capacity and therefore is classified as structural damage or defect. This depends often on the type of damage and on the affected component. Furthermore, damages must at least affect one load-bearing component (not accounting traffic loads) in order to be classified as structural damage, so damages on non-load bearing components e.g. bridge caps or railings are considered defects (see Equation 3).

$$\forall d \exists co (Damage(d) \wedge hasDamage(c, d) \wedge \neg hasLoads(c) \rightarrow Defect(d)) \quad (3)$$

A rule for classifying a structural damage is shown in Equation 4. It should be mentioned that these rules are only valid for a certain type of components, in this case for a roller bearing of a bridge.

$$\forall d \exists co (LongitudinalCrack(d) \wedge \mathrm{RollerBearing(co)} \wedge hasDamage(co, d) \rightarrow StructuralDamage(d)) \quad (4)$$

Similar to Equation 2, an anomaly has been previously identified as longitudinal crack related to the affected component. Since the crack through the roller bearing has a serious impact on the movement and load bearing capacity of the support element the damage is classified as structural damage. However, the same is not necessarily true if another component is damaged by a longitudinal crack, thus the structural assessment requires always both, a classified damage and the affected component.

5.2 Evaluation Rules

When classifying a damage, it is always possible to infer certain parameters that have an effect on the construction. In most maintenance processes the important domains for assessment are the structural capacity, durability and safety. According to (BVBS, 2007) for each domain a factor can be assigned by the inspecting expert, which is based on similar classifications, described in the previous section 5.2. Therefore, these factors can be reasoned by utilizing rules as shown in Equation 5.

$$\forall d \exists co (GapingJoint(d) \wedge \mathrm{ElastomericBearing(co)} \wedge hasDamage(co, d) \rightarrow sFactor(d, 2) \quad (5)$$

In the example, an elastomeric bearing is affected by a gaping joint, which has an impact on the structural capacity. Thus, the related factor is assigned the grade 2. Similar to this, factors for durability and traffic safety are assigned. Consequently, a rule-based classification according to current standards would be feasible. It should be mentioned that common bridge inspection standards often define much more criteria for evaluating grades. More accurate methods for damage assessment, e.g. prognosis of the degradation process or traffic simulations require a greater number of inferred parameters. Despite of its importance, this research neglects the durability and safety and focuses on the structural capacity and the related parameters that could be reasoned by classifying damages. Therefore, the aim of the damage classification is the preparation of mapping the damage information into a structural analysis model to process a system identification utilizing additional monitoring data that reflect the actual construction behavior. Multiple approaches for modeling damages were considered such as the smeared or discrete crack approach (Bažant & Oh, 1983)(Cervenka & Saouma, 1995) as well as reducing the degrees of freedom or movement capacity of damaged support elements Therefore, an additional TBox has been developed, that is used for defining the corresponding mechanical parameters.

By utilizing evaluation rules, these mechanical parameters could be reasoned from specific damage types that affect certain components. Equation 6 shows an example, where a corroded area restricts the movement of a roller bearing.

$$\forall d \exists co \exists mx \exists my \exists mz \exists rx \exists ry \exists rz (HeavyCorrosion(d) \land RollerBearing(co) \rightarrow restrictedMovementX(co, mx) \land restrictedMovementY(co, my) \land restrictedMovementZ(co, mz) \land restrictedRotationX(co, rx) \land restrictedRotationY(co, ry) \land restrictedRotationZ(co, rz)) \quad (6)$$

In this case, the three movement and rotation degrees of a roller bearing are restricted if it is affected by heavy corrosion, which should be ideally modeled as a damage area. Therefore, specific reduction values could be assumed, however since the correct reduction is difficult to evaluate just by non-destructive inspection methods, it is recommended to variate these parameters and perform a system identification according to (Luu et al., 2018).

5.3 Assumption Rules

Despite a comprehensive inspection of the existing construction, often damages remain undetected, which cannot be identified with conventional non-destructive methods, e.g. broken reinforcing elements or cracks that are aggregated in the structure. By utilizing rules, these damages could be assumed based on previously detected damages and their context in the construction and its components. For instance, certain damages could be assumed, if a construction has been built in a specific time, where outdated standards were used. As an example, German bridges that were built before the age of 1972, have a higher risk of being damaged by stress corrosion cracking, due to different standards in dimensioning, e.g. the minimum reinforcement or a different traffic load assumption (Maurer et al., 2012) (see Equation 7).

$$\forall b \exists x \exists d (Bridge(b) \land ConstructionDate(b, x) \land (x < 1972) \rightarrow AssumedSCCDamage(d) \land hasDamage(b, d) \land probabilityFactor(d, 2) \quad (7)$$

When identifying, that the refurbishment of an inspected bridge is dated before 1972, a new damage individual is created as an instance of an assumed damage. In addition, the new individual is assigned to the construction and a probability factor is defined, which represents the occurrence probability of the assumed damage. Since at the time of this publication no studies existed regarding the calculation of these probabilities, instead of a percentage probability, an integer factor is used representatively. In addition to the construction properties, the aggregated components can also influence the damage progression, as shown in Equation 8.

$$\forall b \exists ps \exists x \exists d (Bridge(b) \land hasPrestressingSteel(b, ps) \land SteelType(ps, St\ 145/160") \land crosssectionType(ps, round) \land manufacturer(ps, "Sigma") \land productionDate(ps, x) \land (x < 1965) \rightarrow AssumedSCCDamage(d) \land hasDamage(b, d) \land probabilityFactor(d, 10) \quad (8)$$

In this example, the prestressing steel of the bridge is defined as a product dated before 1965 from a specific manufacturer. According to (BAW, 2006), bridges that contain this type of prestressing steel in their structure, have a significant higher probability of stress corrosion cracking.

In the subsequent system variation and identification, the probability factors are configurable, so that it is possible to exclude low probabilities of certain damage types in order to decrease the amount of variations and thus increase the mass simulation performance. Therefore, for every assumed damage type, the sum of probability factors is formed. This can be achieved by processing a simple SPARQL Query as shown in Listing 1.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX asmptn: <http://www.wisib.de/ontology/damage/dotasmptn#>

SELECT (SUM(?probability) AS ?totalProbability)
WHERE {
	?assumedDamage rdf:type asmptn:AssumedSCCDamage.
	?assumedDamage asmptn:probabilityFactor ?probability.
	FILTER (?probability < 4)
}
```

Listing 1 SPARQL Query for determining the total probability of all assumed stress corrosion cracks with probability value less than four.

6. Conclusions and Future Work

Based on quantifications of detected anomalies, which can be either recorded manually by human experts or by machines, a web ontology could be produced which forms a knowledge database for subsequent information processing together with a linked web ontology of the existing construction.

By applying semantic rules, an initial classification can be processed, whereby additional properties can be inferred through the rule-based assessment of the damages. Furthermore, assumption rules can be applied to reason for undetected damages to be known from past projects. However, these damages can at most be classified as “Assumed Damages”, since their existence need to be proven either by conventional measurement methods or simulation-based system identification approaches, which should be preferred in the context of non-destructive inspections. In processing a system identification, the mechanical parameters of the detected damages are variated and based on the results of the numerical simulation in context with monitored data of the construction. Assumed damages can be concluded and mapped on the structural analysis model for further simulations in an iterative process.

Initial Rules have been prototypically applied on an ontology, which represents an existing bridge construction. Nonetheless, a comprehensive validation of the method is still subject of future research. Furthermore, the generation of variations and their corresponding management needs to be developed for processing a system identification using the assumed damages. Consequently, the approach needs to be validated through the comparison with alternative methods, such as case-based reasoning, convolutional neural networks or frequency resonance method.

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