An Ontological Approach for Pathology Assessment and Diagnosis of Tunnels

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Abstract. Tunnel maintenance requires complex decision making, which involves pathology diagnosis and risk assessment, to ensure full safety while optimising maintenance and repair costs. A Decision Support System (DSS) can play a key role in this process by supporting the decision makers in identifying pathologies based on disorders present in various tunnel portions and contextual factors affecting a tunnel. Another key aspect is to identify which spatial stretches within a tunnel contain pathologies of similar kinds within neighbouring tunnel segments. This paper presents PADTUN, a novel intelligent decision support system that assists with pathology diagnosis and assessment of tunnels with respect to their disorders and diagnosis influencing factors. It utilises semantic web technologies for knowledge capture, representation, and reasoning. The core of PADTUN is a family of ontologies which represent the main concepts and relations associated with pathology assessment, and capture the decision process concerning tunnel maintenance. Tunnel inspection data is linked to these ontologies to take advantage of inference capabilities offered by semantic technologies. In addition, an intelligent mechanism is presented which exploits abstraction and inference capabilities. Thus PADTUN provides the world's first semantically based intelligent DSS for tunnel maintenance. PADTUN was developed by an interdisciplinary team of tunnel experts and knowledge engineers in real-world settings offered by the NeTTUN EU Project. An evaluation of the PADTUN system is performed using real-world tunnel data and diagnosis tasks. We show how the use of semantic technologies allows addressing the complex issues of tunnel pathology inferencing, aiding in, and matching transportation experts' expectations of decision support. The methodology is applicable to any linear transport structures, offering intelligent ways to aid with complex decision processes related to diagnosis and maintenance.

Keywords: tunnel diagnosis, ontology, intelligent decision support systems, linear transport structures

1 Introduction

Transportation systems form an integral part of any modern ecosystem and human society. Effective implementation of maintenance policies and renewal of transport infrastructure, such as tunnels or roads, is an essential part of the significant volume of financial or human investment capital involved (Guler, 2013; Vickerman, 2004). Increasingly, data-driven transport operators are under pressure to provide satisfactory services and efficient methods for their daily travel to consumers who depend on transportation infrastructure. Operational decisions regarding transportation do not only impact the

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level of service for consumers but also cause financial losses to the operating companies due to high repair costs, poor services, and in the worst cases, may cost lives. Many services affecting transportation, including monitoring of various aspects of infrastructure, are data-driven with real-time sensing or manual recording of different key performance indicators (Benvenuti et al., 2017).

The work presented here focuses on railway infrastructure, more specifically tunnel maintenance, though it should also be directly applicable to other tunnels such as road tunnels. Organisations managing a large number of tunnels and underground structures are confronted with the need to guarantee the full safety of use while optimising their overall maintenance costs. This is particularly critical in railway tunnels; for example, in France, the mean age of railway tunnels is 124 years, with 80% of them over 100 years of age. Tunnel experts carry out periodic tunnel inspections leading to the evaluation of a tunnel's global conditions by identification of the main pathologies present based on possible causes in the form of disorders and diagnosis influencing factors (UIC, 2009). This is a complex process, prone to subjectivity, and scales poorly across use cases and domains. Maintenance operations and the impact of a tunnel malfunction can be costly and catastrophic.

Considering the high-risk, critical decision-making process involving multitude and complex decisions faced by human decision makers at transport operators, decision support systems (DSS) can play a key role in this process (Shim et al., 2002). DSS offer technological assistance to decision makers in making better and more well-informed decisions. Decision support systems assist decision makers in obtaining precise and accurate knowledge, to aid in their decision making. Decision makers not only suffer from constraints, such as time and business costs, but may also be overloaded with information. A DSS for railway infrastructure maintenance can help decision makers decrease maintenance costs and increase quality standards (Regulation, 2011; Guler, 2013; Tutcher, 2014; Ingolotti et al., 2004). For tunnel diagnosis, in addition to inferring possible pathologies in individual tunnel portions, it is also important to consider spatial aspects, such as inferring continuous tunnel portions with similar types of pathologies (called here 'pathology stretch inferencing'). The key challenge is to develop an aggregation mechanism to group together individual portions into larger regions of interest based on a similarity of pathologies. This abstraction is extremely important for efficiency reasons. For example, a two-kilometre tunnel with ten metre portions will have 200 portions for tunnel experts to inspect. Hence, an appropriate aggregation resulting in regions of interest and ultimately reducing the number of individual portions to consider, will facilitate and improve the efficiency of the diagnosis process.

To address these challenges, Artificial Intelligence (AI) methods that detect patterns in tunnel inspection data can be used. They can underpin expert engineering systems, such as transportation or tunnelling systems, which employ computational models of domain knowledge. For human–machine interaction in the domains of interest, systematic digitisation of such expertise is of pivotal importance. Ontologies provide a formal specification or description of concepts and their relationships, allowing modelling knowledge in a specific domain. Ontologies have been used in a variety of domains, to capture the structure of the domain, and to support knowledge based reasoning. Some examples of these domains include biomedical, transportation, built environments, and military. Ontologies facilitate the generalisation of concepts, knowledge sharing and reusing. These are crucial especially in domains where the decisions can have high impact (e.g. high cost or loss of life).

An ontological approach to developing a decision support system for tunnel maintenance is presented here. A DSS for Pathology Assessment and Diagnosis of TUNnels (PADTUN) was developed in the EU project NeTTUN by involving tunnel experts and knowledge engineers. PADTUN exploits AI technologies and is applicable to transportation and tunnel engineering; it has been evaluated as an aid for tunnel diagnosis for the French national railway, SNCF. The prime drivers for PADTUN include: (a) computer-aided diagnosis, (b) reduction of labour and maintenance costs, (c) passenger and infrastructure protection, (d) capturing and preserving tacit expertise or the intuition of transportation experts, and (e) training next-generation of transportation inspectors.

Our work makes a number of key contributions to engineering applications of artificial intelligence: (a) by providing a systematic methodology for how to adopt semantic technologies to address pressing needs of infrastructure maintenance — an extremely important domain in our modern society; (b) by adopting the methodology in the context of tunnel maintenance and validating it in a practical application driven by a real world problem at the French national railway company SNCF; (c) by working closely with domain experts at SNCF, illustrating how ontologies can provide a vehicle to articulate and capture tacit knowledge of complex decision making, enabling organisations to preserve vital expertise accumulated with years of experience. The tunnel maintenance ontologies presented here are the first ever ontologies developed for the domain of tunnel diagnosis and maintenance. By linking these ontologies to tunnel inspection data and utilising ontological reasoning, we present a novel decision support system that provides intelligent ways to aid with complex decision processes related to tunnel diagnosis and maintenance. A detailed evaluation study, based on data of 46 existing tunnels (total of 50 km), has validated the ontologies and the output of the reasoning in a real-world decision support context. Crucially, the knowledgedriven approach presented in this paper provides a transparent and explainable artificial intelligence to augment human decision making. While the practical examples here are in railway tunnels, the approach is applicable to similar linear transport structures, such as road tunnels or bridges.

This paper is a significantly extended version of a paper which was awarded the Best In-Use paper at the Extended Semantic Web Conference ESWC2015 (Thakker et al., 2015) – we have expanded the detail of the main components, have provided a systematic description of the methodology so that it can be followed in broader domains, and have added a detailed evaluation with real world tunnel data. The paper is structured as follows. Firstly, we position our work in the relevant literature and justify the main contribution (Section 2). Section 3 outlines the technical architecture of the PADTUN system, followed by presentation of the PADTUN ontologies (Section 4), pathology inferencing (Section 5) and pathology stretch inferencing (Section 6). The PADTUN interface and user interaction with the system is described in Section 7. Section 8 presents the PADTUN evaluation with existing tunnel data which validates the approach and shows its applicability in real world contexts. The paper concludes with a discussion on the generality and broader applicability of the proposed approach, linking it with current data-driven approaches.

2 Related Work

This section will position our work in the relevant literature, including: DSS, ontology-based approaches to develop DSS, and similar application domains where such DSS systems are applied, including transportation and built environments.

DSS is defined as: ‘‘the area of the information systems discipline that is focused on supporting and improving managerial decisionmaking’’ (Arnott and Pervan, 2005a; Holsapple and Whinston, 2013). DSS technology and applications have existed since the early 1970s (Borne et al., 2003). DSS systems are traditionally divided into six different types: model-driven DSS, data-driven DSS, communications-driven DSS, document-driven DSS, intelligent DSS, and knowledge-driven DSS (Power, 2004; Bhargava et al., 2007). Intelligent DSS is a category of DSS which incorporates intelligent functionalities such as the use of AI tools and techniques to provide decision support.

Semantic Web-based approaches are becoming increasingly common in developing such intelligent DSS with a large proportion of work in the applied domain (45% as opposed to 4% theoretical work) (Blomqvist, 2014). The Semantic Web aims to extend the current World Wide Web model with machine-interpretable semantics (W3C). In the Semantic Web, ontologies define the concepts and relationships (also referred to as ‘‘terms’’) used to describe and represent an area of concern (He and Ling, 2006). Ontology engineering is used to systematically organise domain experts' knowledge in critical areas such as transportation or medical diagnosis. The development of DSS has a strong focus on models, including multi-dimensional models, data cubes, and Online Analytical Processing, making Semantic Web methods a good fit as a base technology (Blomqvist, 2014). One of the prominent application areas within the development of DSS where Semantic Web technologies have been applied is in making the domain knowledge required for making decisions explicit (Power and Sharda, 2007; Bruaux and Saad, 2009; Rospocher and Serafini, 2012). Another prominent aspect where Semantic Web technologies are utilised is fulfilling the requirement of the DSS and decision maker to have access to heterogeneous data (Antunes et al., 2016; Bose and Sugumaran, 2007; Jung, 2009). There are many examples of Semantic Web-based DSS in the critical areas of military planning (Valiente et al., 2011; Louvieris et al., 2010), emergency decison support (Kai et al., 2008), legal processes (Paschke and Bichler, 2008; Beach et al., 2015), and the financial sector such as the consumer markets (Kwon, 2006) and financial services (Wang et al., 2004). There is also a large body of work in the areas of health and clinical domains (González et al., 2009; Sanchez et al., 2011). For example, Yang et al. use ontologies for information collection and patient representation (Yang et al., 2009). Rodríguez-González et al. provide a well-structured ontology for automated diagnosis in the medical field and a three-fold formalisation based on Description Logics with the use of Semantic Web technologies (Rodríguez-González et al., 2012). As another example, Abidi presents a conceptual framework for ontology-based knowledge representation and merging of Clinical Pathways of comorbidities (Abidi, 2008). Del Mar Roldan-Garcia et al. propose a novel ontology to represent liver patient cases and build a proof of concept for clinical experience sharing platform based on semantic reasoning (del Mar Roldán-García et al., 2018).

There are DSS which utilise data for predictions and insights into the monitoring and inspection of railway systems (Ward et al., 2011; Charles et al., 2008; Garcı et al., 2003; Lai et al., 2010). There is a growing body of work using semantic web technologies for built environment solutions. A survey paper (Abanda et al., 2013) on the topic has identified a gradual shift from traditional construction applications to Semantic Web sustainable construction applications. Benvenuti et al. (2017) propose a framework to ease the development of a monitoring system in the public transport domain; their approach is based on the ontological representation of the knowledge regarding indicators and their formulas, business objectives, dimension analysis and their relation with the Transmodel (the European reference data model for public transport information systems). In addition, a Prolog-based reasoning framework provides logic functionalities to interactively support designers in a set of common design tasks: the choice of the most suitable indicators for the performance monitoring needs at hand, the definition of new indicators and the identification of the minimal set of Transmodel modules needed to calculate them. Hu et al. (2015) present a framework to determine optimal maintenance plans for large networks with many bridges. The objective is to minimise disruption, specifically, the extra travel distance caused by potential bridge failures, over a planning horizon and under a budget constraint. The work focuses on using simulation-based numerical optimisation techniques. Saa et al. (2012a,b) present an ontology and knowledge-based rules to model complex electrification structures in the railway domain. The outcome of this work is an intelligent computer-aided design tool to facilitate safe and cost-effective infrastructure.

An alternative approach is data-driven, rather than simulating scenarios; such an approach aligns with what happens in practice. To understand the domain, a knowledge model in the form of a domain ontology can be used. An ontology of tunnel safety features has been studied in Cristani (2003) focusing on providing an analytical description of the basic structure of tunnel safety features. An important contribution to the field, the ontologies do not appear to be based on any existing safety frameworks for tunnels, and are not evaluated. In comparison, our PADTUN ontologies, cover a different domain related to tunnels, and is based on the literature as well as experts in the field, and is evaluated. We also intended that our ontology development should be reusable. A knowledge management system for building underground works (Faure et al., 2006) uses 'trees of words' to represent ontologies, hence limiting its reusability as these are not a standard representation. Min and Zhewen (2014) focus on a complementary problem of data integration while developing a tunnel construction information retrieval system. The integration of data from heterogeneous sources is one of several technical challenges during the tunnel construction. The authors propose a tunnel data organisation method driven by an ontology, which is suitable for data reorganisation and reasoning. All these existing works that use ontologies tend to focus on the product, i.e. a domain model, instead of also focusing on the methodology for creating the ontology, where using a defined methodology offers transparency to the ontology creation process. We utilise a standardised Web Ontology Language to design our ontology and share our ontology development methodology (which is based on the METHONTOLOGY (Mor-Yaroslavtsev and Levchenkov, 2011) methodology).

Our work presents a novel DSS, PADTUN, for tunnel diagnosis and maintenance using emerging Semantic Web technologies. PADTUN assists tunnel experts in making decisions about a tunnel's condition with respect to its disorders and diagnosis influencing factors. PADTUN also allows reviewing regions of interest with similar pathologies. The PADTUN ontologies are the first ever ontologies developed for the domain of tunnel diagnosis and maintenance. These ontologies are used to model tacit knowledge from tunnel experts and capture the existing decision process concerning maintenance of tunnels and provide a context model for automated decision support. In PADTUN's development, heterogeneous data is annotated using ontologies to take advantage of the inference capabilities offered by semantic technologies. A further application of semantics is in the use of PADTUN ontologies for calculating homogeneous portions in order to identify regions of interest. In particular, semantics plays a key role in detecting continuity by considering semantic similarity between pathologies represented as concepts. With this work, we contribute to intelligent systems research by applying semantic technologies in urban and infrastructure planning and maintenance, a domain that is starting to receive attention from the Semantic Web community (Lécué et al., 2012, 2014).

3 PADTUN Architecture

To assist with the complex process of tunnel diagnosis we have developed the PADTUN decision support system. The users are tunnel experts who make decisions about a tunnel's condition by identifying what pathologies exist and in which part of the tunnel. For this, experts use tunnel inspection data that indicates observed tunnel disorders, as well as tunnel contextual data which records influencing factors that impact the development of pathologies. We adopt a knowledge-driven approach which utilises ontologies to indicate the main concepts in tunnel inspection and diagnosis, together with relationships between these concepts that are considered when deciding on the existence of pathologies. The overall architecture of the PADTUN system is presented in Fig. 1, following a three-tier model including layers for data, processing, and presentation.

Data layer. Transport infrastructure asset owners in general, and tunnel asset owners specifically, manage inspection databases that record the provenance of data related to inspections and any repairs. This data generally contains information about any disorders, i.e. observations and measurements that may indicate abnormalities (e.g. cracks or leaking in the tunnel) and contextual factors, i.e. facts that can have catalytic effect on abnormalities (e.g. tunnel age or tunnel traffic). PADTUN imports such inspection data in the form of XML (Extensible Markup Language)[2] files. This provides independence from the specific systems for data collection, as XML is a well-established standard for exchange of data over the web and database-to-XML converters are provided by most data management systems.

In addition to inspection data, PADTUN brings a domain-specific knowledge model, encoded in the form of a family of ontologies. To facilitate generality and wider adoption, a systematic ontologydriven data approach is followed. This includes encoding the domain knowledge in ontologies using a widely accepted standard, the Web Ontology Language (OWL).[3] The PADTUN ontologies, which represent knowledge about tunnel disorders, diagnosis influencing factors, lining materials and pathologies, have been developed with the active involvement of tunnel experts. For this, an ontology engineering methodology has been adapted defining iterative steps of development and evaluation. The PADTUN ontologies and ontology engineering methodology are described in detail in Section 4.

Another component in the data layer is a semantic repository that provides the mapping between ontology concepts and data and allows inferencing for automated reasoning. To ensure domain independence and wider adoption of the PADTUN architecture, in addition to using an established standard in OWL, we took advantage of widely available triple store frameworks.[4] Specifically, OWLIM was chosen due to scalability reasons (Thakker et al., 2010)[5] as the system is required to reason over a large number of tunnels and amount of inspection data. The system also contains a relational database to store inspection and result data for caching purposes.

Application layer. The semantic repository is queried using intelligent processing to infer tunnel pathologies. This is done per tunnel portion — the main unit of length for tunnel inspection (this is usually defined by the tunnel owners and can vary across owners or countries, e.g. in the SNCF case presented in the evaluation below, a tunnel portion was 10 metres). For each portion, the pathology inferencing includes: (a) inferring pathologies based on noted disorders; (b) inferring pathologies based on tunnel influencing factors; and (c) a cumulative model that aggregates the two inferred lists by using a weighting mechanism; the result is an ordered list of likely pathologies.

Based on the pathology detection per tunnel portion, an additional intelligent mechanism was developed that aggregates the tunnel portions to capture the stretch of a pathology family across the tunnel. We call such stretches Regions of Interest (ROIs). The mechanism for identifying ROIs is based on interval extrapolation and pathology similarity comparison. The ROIs provide an overview of the condition of the tunnel and allow answering questions like: 'Which stretch of the tunnel has lining and/or ground degradation?', 'Is there a stretch in the tunnel where the lining is ageing?', etc. Such questions are key when decisions about tunnel repair are taken.

Driven by the requirement for interoperability and modularity, the automated reasoning components in the application layer are implemented following a well-established web services model —

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

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

[4] https://www.w3.org/2001/sw/wiki/Category:Triple_Store

[5] OWLIM has evolved to GraphDB (http://graphdb.ontotext.com/) used in industrial semantic web systems.

Representation State Transfer (REST) services. Web services allow separating the processing features from the interface features, and are the de-facto standard for modern web-based applications. RESTful services provide uniform interface semantics to exchange messages between independent software components that encapsulate specific functionality.5 The pathology inferencing and ROI detection services are presented in Sections 5 and 6 respectively.

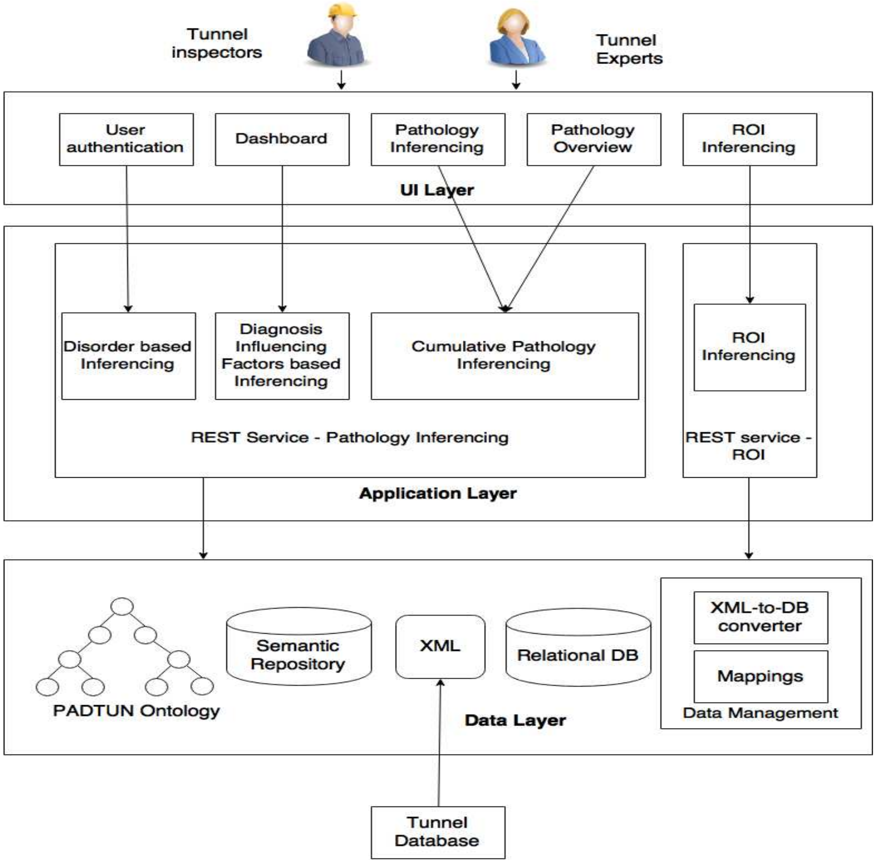


Fig. 1. PADTUN system architecture – a knowledge-driven three tier model, comprising a Data Layer, an Application Layer, and a User Interface (UI) Layer.

User interface (UI) layer. The user interface allows tunnel experts to interact with the decision support system to get insights about the condition of the tunnel, as derived from the tunnel inspection data and the tunnel influencing factors. The users can upload inspection data about a specific tunnel and get: (a) a dashboard that shows all tunnel portions and the possible pathologies associated with each portion — this allows in-depth examination of the diagnostic component of the system and offers the finest level of granularity; (b) a pathology inferencing window which renders the output of the pathology aggregation which is weighted based on pathology inferencing frequencies — this allows a middle level of granularity that offers an overview of pathologies but hides in-depth inspection data, for which the user can go to the dashboard; (c) a ROI inferencing interface which gives a tunnel overview indicating the regions where specific pathology families have been detected.

A crucial feature of the PADTUN DSS user interface is transparency — not only presenting automatically derived information about the condition of the tunnel to facilitate humans in performing complex tunnel diagnosis tasks, but also providing a means to show why a specific condition has been detected. In this way, the system is seen as a computational assistant in the human decision process based on data and knowledge it has been provided with, not as a decision making system that simply suggests decisions that should be taken. Moreover, when taking critical tunnel maintenance decisions, tunnel experts may use additional data that is not currently included in the system (e.g. traffic data, climate data, nearby services data). The PADTUN UI layer, which is presented in Section 8, is fully independent from the data layer and the processing layer.

4 PADTUN Ontologies

4.1 Ontology Engineering Methodology

The PADTUN system is underpinned by a knowledge model in the form of an ontology that allows reusability and wider deployment of our knowledge-driven approach. Ontologies are the key components of semantic web systems, and have been studied extensively by the semantic web research community (He and Ling, 2006). This community has created and tested methods and tools to support the ontology engineering process (Gómez-Pérez et al., 2004); PADTUN ontologies have been developed using the METHONTOLOGY (Mor-Yaroslavtsev and Levchenkov, 2011) methodology.

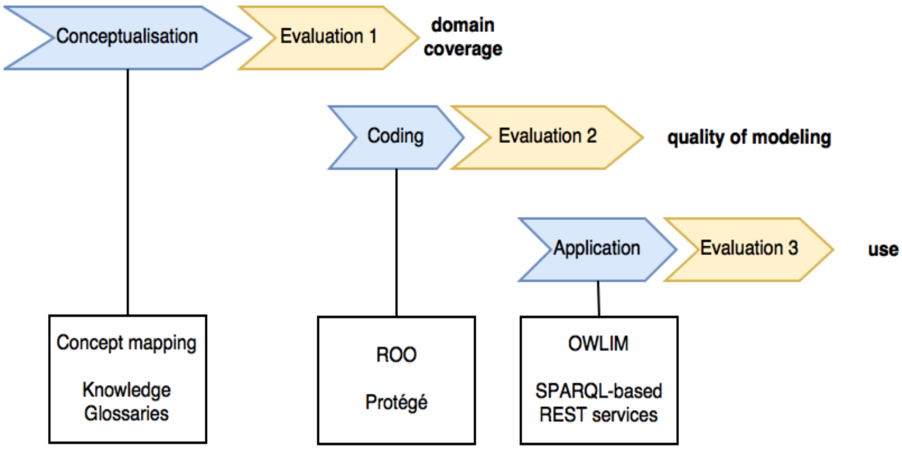


Fig. 2. Overview of the PADTUN ontology creation and application.

This methodology enables ontology building at a conceptual level, compared to implementation level. The methodology consists of different activities or steps: a specification step to define the scope and purpose of the ontology and develop a formal or informal ontology specification document in written natural language; a knowledge acquisition step to elicit knowledge from the literature or experts; a conceptualisation step to encode knowledge as knowledge glossaries; an implementation step to encode knowledge in a standardised ontology language such as OWL; and an evaluation step to carry out technical and application judgement of the ontology (Mor-Yaroslavtsev and Levchenkov, 2011). Fig. 2 illustrates how we have adopted the METHONTOLOGY with the different stages of ontology research and development. We have identified the technologies and techniques used for conceptualisation of ontology to its software implementation. The culmination of this process is the demonstration of a real-life tunnel diagnosis application using semantic web techniques. Evaluation is done at each stage to gauge strict adherence to the specification requirements and system performance. For example, at the conceptualisation stage, evaluation ensures domain coverage, at the coding stage, evaluation helps with maintaining the quality of modelling and picking any technical discrepancies, and at the application stage, it demonstrates feasibility of the approach. Tunnel ontology conceptualisation and pathology inferencing for tunnel diagnosis are presented in following sections, but first, we will discuss the ontology requirements specific to tunnel diagnosis.

4.2 Specification

Scope and purpose. NeTTUN use cases helped us to define the scope and purpose of the ontologies and provided a reasonably well-defined target. For software in critical domains, such as a semantic DSS for tunnel diagnosis, formal ontology requirements should be satisfied in addition to the application ones (Su et al., 2009). The ontologies need to capture the existing decision process concerning the diagnosis of tunnels, to provide a context model for automated decision support. This conceptual model should include disorders observed during the inspections, common tunnel pathologies and the influencing factors. This knowledge also needs to be classified and linked, in order to identify typical associations of disorders for each pathology and typical influencing factors for pathologies development and evolution.

Knowledge sources. The ontologies were designed based on the knowledge of experts within the NeTTUN project. To ensure a wide range of use and generality, extensive literature in the area was also consulted (UIC, 2009; Sandrone and Labiouse, 2010; SNCF, 2008; UIC, 2013; AFTES, 2005; CETU, 2004; Sandrone, 2008; UIC, 2005, 2008; CIRIA, 2009; US Department of Transportation, 2005).

4.3 Conceptualisation

This activity requires that the domain knowledge is structured in a conceptual model describing the problem and its solution in terms of a domain (Fernández-López et al., 1997; Uschold, 1996). We used a number of methods for knowledge elicitation including expert interviews, brainstorming sessions using tools such as Concept Maps to facilitate the conceptualisation process. The initial conceptualisation focused on the elicitation of the top-level ontology concepts.

Top level concepts. Several tunnel type classifications were considered. For instance, tunnels can be classified regarding their operational use, construction method, age and other characteristics. The proposed classification regarding the PADTUN scope is based on an elementary part of a tunnel, an atomic portion, called here a Tunnel Portion. A Tunnel Portion can be defined as ‘‘an elementary part of the tunnel with all the necessary elements that enable a diagnosis to be made’’ (UIC, 2009; SNCF, 2008). In this respect, a Tunnel Portion presents geology, geometry, and structural characteristics like lining or repair features.

A Tunnel Portion is derived from larger tunnel stretches. Because the scope of the ontologies is for maintenance, these larger tunnel stretches have been defined as Tunnel Inspection Stretch, corresponding to tunnel lengths where an inspection has been carried out. A Tunnel Inspection Stretch has one location, and it is inspected at least once. Furthermore, regarding the geology within a Tunnel Inspection Stretch, one or more Tunnel Geo Stretch can be identified, each one characterised by one geology. This conceptualisation is presented as a concept map in Fig. 3.

Pathologies. A pathology is a problem that causes tunnel disorders; it is also the link between the disorders and its causes. Pathologies provoke tunnel degradation, which manifests itself in a combination of disorders, often more than one. Considering tunnel experts' interviews and the literature on the subject, the most common pathologies were identified and classified according to these degradation processes. These were collected from the experts as a knowledge glossary (Fernández-López et al., 1997; Uschold, 1996).

Tunnel disorders. Disorders are disturbances in the expected quality level of a tunnel, being subjected to evolution. Disorders are also symptoms of pathologies. A classification of disorders was collected from the experts as a knowledge glossary. The associations between disorders and pathologies are provided as a table (see Fig. 4); there were in total 227 such associations provided by the experts.

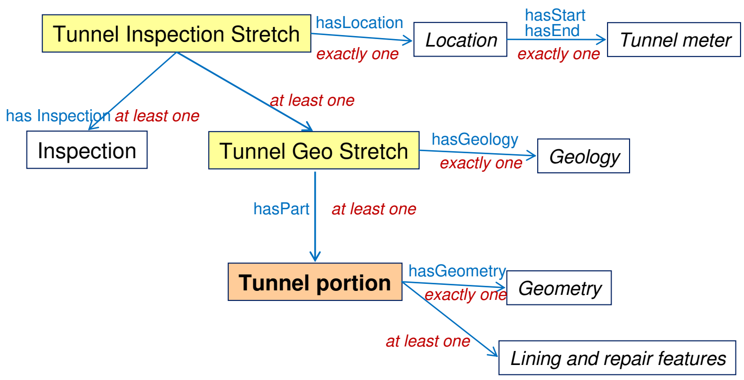


Fig. 3. Concept Map with the top level concepts related to Tunnel.

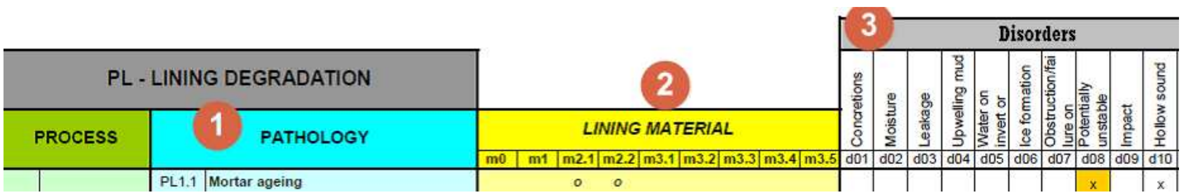


Fig. 4. Illustration of the association between pathologies and disorders with Mortar ageing pathology as an example (1). (2) shows the coded list of lining material that has to be present to manifest Mortar ageing (3) shows the disorders i.e. ''potentially unstable'' (structure) that have to be present to manifest mortar ageing. The orange coloured cell signifies that this disorder is a typical disorder for this pathology.

Diagnosis influencing factors are factors representing all elements influencing tunnel degradation, which are considered by the expert(s) when making decisions. The associations between pathologies and diagnosis influencing factors were provided as a spreadsheet by the domain experts. There were in total 78 associations provided by the experts. Factors can be classified according to their two main functions in the diagnosis decision process. ***Pathology factors.*** These are elements having a direct influence on pathology development, either because they participate in the cause of a pathology, or are influencing the evolution speed of the pathology reaction. ***Decision factors.*** These are other elements taken into account by experts when assessing the tunnel future conditions (risk factors), but not directly participating in the pathology reaction. They are the elements that allow the experts to assess the impact level of pathology evolution on a tunnel portion regarding its characteristics (lining material, tunnel shape, etc.) or its history. Diagnosis influencing factors can be classified in three main categories. ***Environmental factors*** are elements related to the site, such as ground conditions, or surrounding constructions. ***Construction related factors*** are elements such as lining features or construction methods. ***Operation related factors*** are elements influencing degradation linked to tunnel maintenance operations.

4.4 Logical Encoding

The process of transformation from conceptual form to logical form involved knowledge engineers using concepts and relationships identified in Glossary of Terms and using a Controlled Natural Language (CNL) based authoring tool (Bao et al., 2010), ROO (Dimitrova et al., 2008; Denaux et al., 2011) to transpose the conceptual model in CNL. ROO then translates the CNL formulation into its corresponding Web Ontology Language (Baader, 2008; McGuinness and Van Harmelen, 2004) needed for machine reasoning. Fig. 5 shows the upper ontology of Tunnel with linkages to other major concepts from the domain model such as Tunnel Type, Tunnel Geo Stretch, and Pathology. The upper level captures that a Tunnel Portion can have disorders, influencing factors, lining materials.

Fig. 6 shows the representation of pathologies and instances based on degradation types: the instances form the lowest level of the hierarchy in Fig. 6 (labelled with diamonds) and the other nodes denote pathology classes (labelled by ochre circles). Regarding the causes of the degradation (the origin of the problem), two broad *families of pathologies* were identified distinguishing based on their origin. They were (a) *ground degradation pathologies* (if pathologies occur in the ground surrounding the tunnel) and (b) *lining degradation pathologies* (if pathologies occur with the lining) (Sandrone and Labiouse, 2010; SNCF, 2008). Fig. 7 depicts how an association between a disorder and a pathology is represented in the ontology. This example shows how the rule provided by the experts in a table (see Fig. 4) is represented in the ontology. Similarly, Fig. 8 illustrates an association between a pathology and a diagnosis influencing factor and other contextual information such as the level of influence.

To facilitate the evolution of the PADTUN ontologies, they were developed as a group of smaller but interlinked modular ontologies (Stuckenschmidt et al., 2009). Table 1 presents a summary of the ontological features of the PADTUN ontologies with size, expressivity (Horrocks et al., 2000), and complexity of the core knowledge captured by axioms. In particular, PADTUN ontologies utilise OWL features such as sameAs, disojointWith, and equivalentClass.

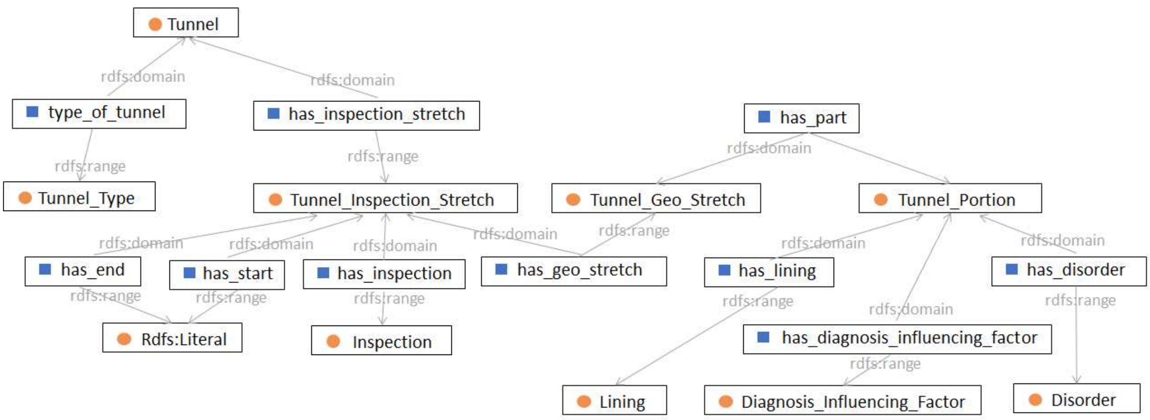


Fig. 5. PADTUN Upper Ontology.

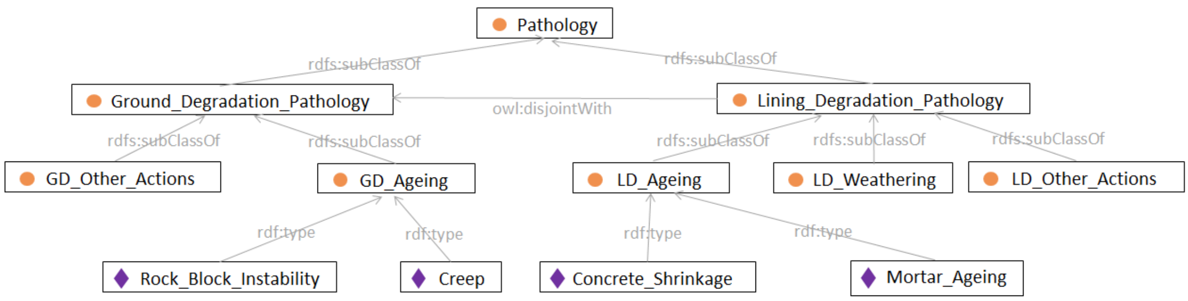


Fig. 6. Partial representation of pathologies classification based on degradation types.

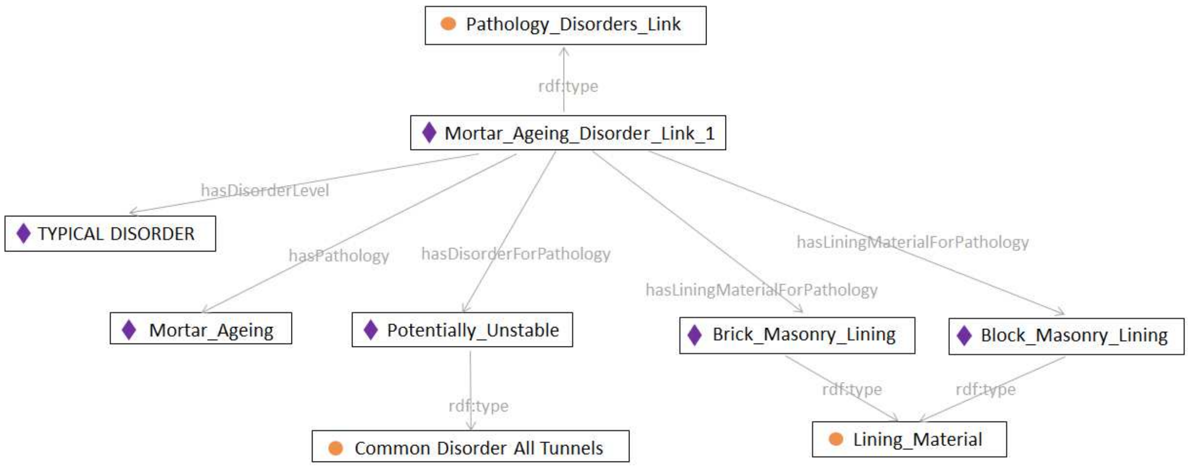


Fig. 7. Illustration of an association between a pathology and a disorder.

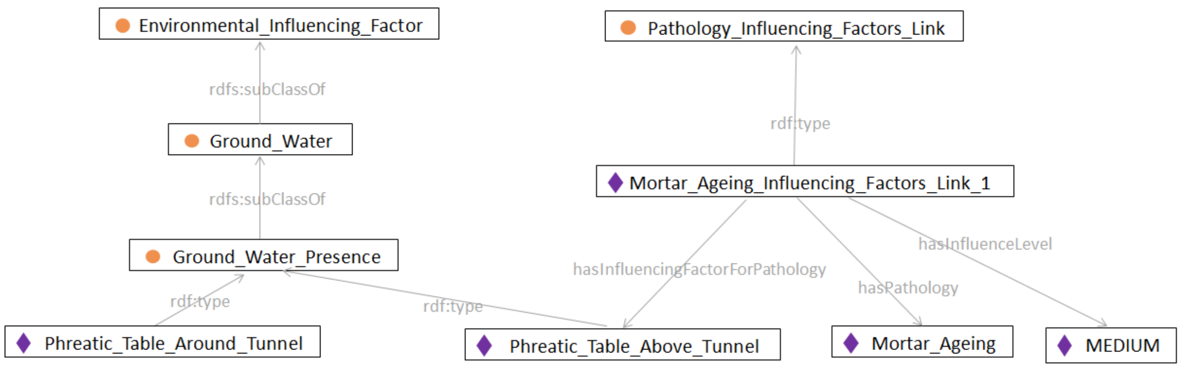


Fig. 8. Illustration of an association between a pathology and a diagnosis influencing factor.

Table 1. PADTUN ontologies features

Feature	Value
No of Classes	125
No of Properties	49
No of Individuals	590
No of Axioms	3981
DL Expressivity	ALEHO

5 PADTUN Ontologies

Pathology and ROI inferencing services are the two central components of the PADTUN application layer. Pathologies, the focus of this section, are inferred in two steps: i) by inferring associations between disorders, and pathologies; and ii) by inferring associations between diagnosis influencing factors and pathologies.

The Disorder-based pathologies component of the pathology inferencing service finds all the pathologies with disorders and lining materials present in the tunnel portion under inspection and ranks pathologies according to the typicality of the disorders. This inference involves SPARQL queries[6].

The Diagnosis Influencing Factors-based Pathology component finds all the pathologies for the diagnosis influencing factors present in the tunnel portion under inspection and ranks them according to their influence level. Furthermore, a check is made if all the necessary influencing factors for a pathology are present in the portion under investigation. If they are not, the pathology is removed from the final list and the ranking is adjusted accordingly. This inference involves SPARQL queries to infer associations and to check the necessary conditions.

The pseudo code of these two components is presented in Fig. 9. The weights (*m* and *n* in the pseudo code) were set by series of interaction with the experts. The values $m=4$ and $n=1$ were found to be the best according to experts' judgement based on three tunnels. We validated this further with seven tunnels and the values were found to be suitable without requiring further adjustments.

The Cumulative pathologies component combines the results of the previous two components by aggregating the score of pathologies in both the lists (*disorder-based pathology list* & *influencing factor-based pathology list).*

[6] SPARQL is the W3C standard query language and protocol for Semantic Web and ontologies. .

```
Disorder-based Pathologies

read disorders, lining materials for a tunnel portion, m, n; m = points awarded for
typical disorders, n= points awarded for normal disorders

for each disorder in disorders
   for each lining material in lining materials
      find pathologies, disorder level with given disorder and lining material
      store pathology, disorder level in a pathology list 1
   end for each
end for each

for each pathology in pathology list 1
   if disorder level = TYPICAL
   then
       score = score + m;
       store pathology, score in disorder-based pathology list
   else
       score = score + n;
       store pathology, score in a disorder-based pathology list
   end if
end for each

sort disorder-based pathology list on score in descending order
```

```
Diagnosis Influencing Factors-based Pathology

read diagnosis influencing factors list 1 for a tunnel portion m, n; m = points awarded
for high influencing factors, n= points awarded for medium influencing factors

for each diagnosis influencing factor in diagnosis influencing factors list 1
   find pathologies, influence level with given diagnosis influencing factor
   store pathology, influence level in pathology list 1
end for each

for each pathology in pathology list 1
   if influence level = HIGH
   then
      score = score + m;
      store pathology, score in pathology list 2
   else
      if influence level = MED
      then
         score = score + n;
         store pathology, score in pathology list 2
      end if
   end if
end for each

for each pathology in pathology list 2
   find necessary influencing factors for pathology
   store in influencing factors list 2
   if subset (influencing factors list 2, influencing factors list 1)
   then
      add pathology in influencing factor-based pathology list
   end if
end for each

sort influencing factor-based pathology list on score in descending order
```

Fig. 9. Pseudo-code of the algorithm for inferring pathologies using the PADTUN ontologies.

6 Pathology Stretch (ROI) Inferencing

Based on the pathology detection per tunnel portion, an additional intelligent mechanism was developed that aggregates tunnel portions to capture the stretch of a pathology family across the tunnel. We call such stretches *regions of interest* (ROIs). One of the decision support aspects of PADTUN is to identify ROIs concerning pathologies. In practice, tunnel experts intuitively abstract

ROIs and in doing so aggregate tunnel portions that have the same types of pathologies that are contiguous, or nearly so – i.e. small gaps are allowed in which the pathologies present are not similar to those on either side of the gap. However, it was not clear at the outset how the experts themselves infer ROIs once pathologies per portion were identified. Hence, a mock-up of several possible alternatives was presented to the experts in order to identify the best way of inferring ROIs. We now present the formal definitions for these alternative ways to define and calculate ROIs.

Let T denote a tunnel comprised of a set of tunnel portions and let top(k,p) denote the set of the top k ranked pathologies for an individual tunnel portion p. Then $X \subseteq T$ is *region of interest* if it is contiguous (i.e. $X = \{p_1 \ldots p_m\}$, *where* p_i *is immediately before* p_{i+1} *for* $i=1 \ldots m-1$) and the pathologies are *homogeneous* in a sense to be defined below, but allowing that there may be small gaps which are inhomogeneous.

We determine the degree of *homogeneity* in an ROI by determining which pairs of tunnel portions p_1, p_2 a given predicate $\Phi(p_1,p_2)$ is true of; we discuss possible definitions of $\Phi(p_1,p_2)$ below. We can then define an aggregation predicate $R_{\Phi,n}(X)$ which must be true of an ROI X, where X is a contiguous set of tunnel portions, and n is the maximum non homogenous gap allowed:

$$R_{\Phi,n}(X) \equiv \exists\,(p_i \in X)\ \forall (p_j \in X)\ [\mathrm{dist}(p_i, p_j) \geq n \Rightarrow \Phi\left(p_i, p_j\right)]$$

where $\mathrm{dist}(p_i, p_j)$ gives the distance between the two tunnel portions p_i and p_j (if p_i and p_j are adjacent—so there is no gap -- then $\mathrm{dist}(p_i, p_j) = 1$).

We considered the following definitions for $\Phi(p_1,p_2)$:

Portions with (Approximately) Equal Pathologies $\Phi_{=,\ \approx}$. Two tunnel portions p_1 and p_2 are deemed to have '*equal*' pathologies when they share the same pathologies: $\Phi_{=}$ is thus defined as:

$\Phi_{=}(p_1,p_2) \equiv top(k,p_1) = top(k,p_2)$.

Two tunnel portions p_1 and p_2 are deemed to have '*approximately equal*' pathologies if all their pathologies are semantically similar:

$$\Phi \approx (p_1,p_2) \equiv [\forall\ (o_1 \in top(k,p_1)) \rightarrow \exists (o_2 \in top(k,p_1))\ similar(o_1,\ o_2)] \wedge$$

$$[\forall\ (o_2 \in top(k,p_2)) \rightarrow \exists (o_1 \in top(k,p_2))\ similar(o_1,\ o_2)]$$

Various notions of semantic similarity can be considered for *similar*(o1,o2), see for example the distance based metrics in Raimond et al. (2009). However, in consultation with the domain experts we arrived at the following definition –two pathologies are *similar* if they are both members of the same pathology *family*, i.e. one of the two immediate descendants of the class Pathology in Fig. 10: Ground Degradation Pathology or Lining Degradation Pathology. This is because they regarded each of these families as being quite distinct, but then with various variations in the possible fine-grained pathologies within each of the two families. In our discussions with the experts we also called this condition "Portions with pathologies in the same family", R_{Φ_F}.

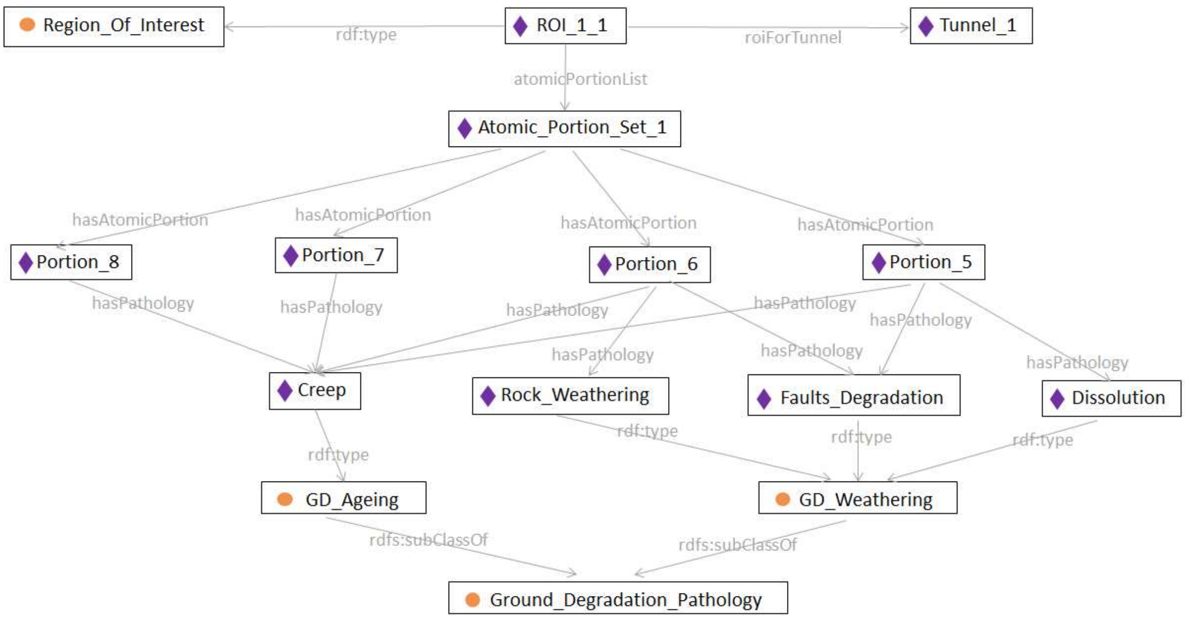


Fig. 10. Ontological representation of one of the resultant ROIs (selection: $n = 1$ and R_{Φ_C}).

Portions with (Approximately) Incorporating Pathologies **($\Phi_{\subseteq}$, $\Phi_{\tilde{\subseteq}}$).** One set of pathologies '*incorporates*' another set of pathologies if it contains all the pathologies that the other set of pathologies has, i.e.

$$\Phi_{\subseteq}(p_1,p_2) \equiv (top(k,p_1) \subseteq top(k,p_2) \wedge top(k,p_1) \neq \emptyset) \vee (top(k,p_2) \subseteq top(k,p_1) \wedge top(k,p_2) \neq \emptyset).$$

Also, one set of pathologies is '*approximately incorporating*' another set of pathologies if there exists some set of concepts in one that are semantically similar to another so that one set of observations contain all the observations that the other observation has, i.e.

$$\Phi_{\tilde{\subseteq}}(p_1,p_2) \equiv [\forall(o_1 \in top(k,p_1)) \rightarrow \exists(o_2 \in top(k,p_2))\ similar(o_1, o_2)]$$

Portions with (Approximately) Overlapping Pathologies **($\Phi_{\cap}$, $\Phi_{\tilde{\cap}}$).** One set of pathologies '*overlaps*' another set of pathologies if it contains only some pathologies that the other one has and vice versa:

$$\Phi_{\cap}(p_1,p_2) \equiv (top(k,p_1) \cap top(k,p_2)) \neq \emptyset \wedge \neg \Phi_{\subseteq}(\{p_1,p_2\}).$$

Also, one set of pathologies '*approximately overlaps*' another set of pathologies if it contains some pathologies that are semantically similar to the pathologies from the other tunnel portion and vice versa, i.e.

$$\Phi_{\tilde{\cap}}(p_1,p_2) \equiv [\exists(o_1 \in top(k,p_1))\ \exists(o_2 \in top(k,p_2))\ similar(o_1, o_2)] \wedge$$

$$[\forall(o_2 \in top(k,p_2) \rightarrow \exists(o_1 \in top(k,p_2))\ [\ similar(o_1,o_2)]\ ] \wedge \neg \Phi_{\tilde{\subseteq}}(\{p_1,p_2\})$$

Example. Consider a tunnel (see Fig. 11) with ten tunnel portions. The observations consisting of pathologies on each of these ten portions are given in the figure with $O = \{d_i,\ldots,d_n\}$; where d_1=Mortar

Ageing; d_2= Dissolution; d_3=Creep; d_4= Faults Degradation; d_5=Rock Weathering and d_6=Swelling. It is also given that d_2 and d_6 are semantically similar, i.e. *similar*(d_2, d_6). A domain expert can then tailor what they would like to view as region of interest by manipulating two criteria from the aggregation function: (a) allowed gap(n) and (b) predicate ($\Phi(p_1,p_2)$) to use. **Fig.** 11 shows various ROIs under different selections. For example, when the selection is $n=1$ and the predicate for portions with equal observations ($\Phi_=$) is selected (first row, **Fig.** 11), the resultant eight ROIs are: $\{\{p_1, p_2\},\{p_3\},\{p_5\}, \{p_6\}, \{p_7\}, \{p_8\}, \{p_9\}, \{p_{10}\}\}$.

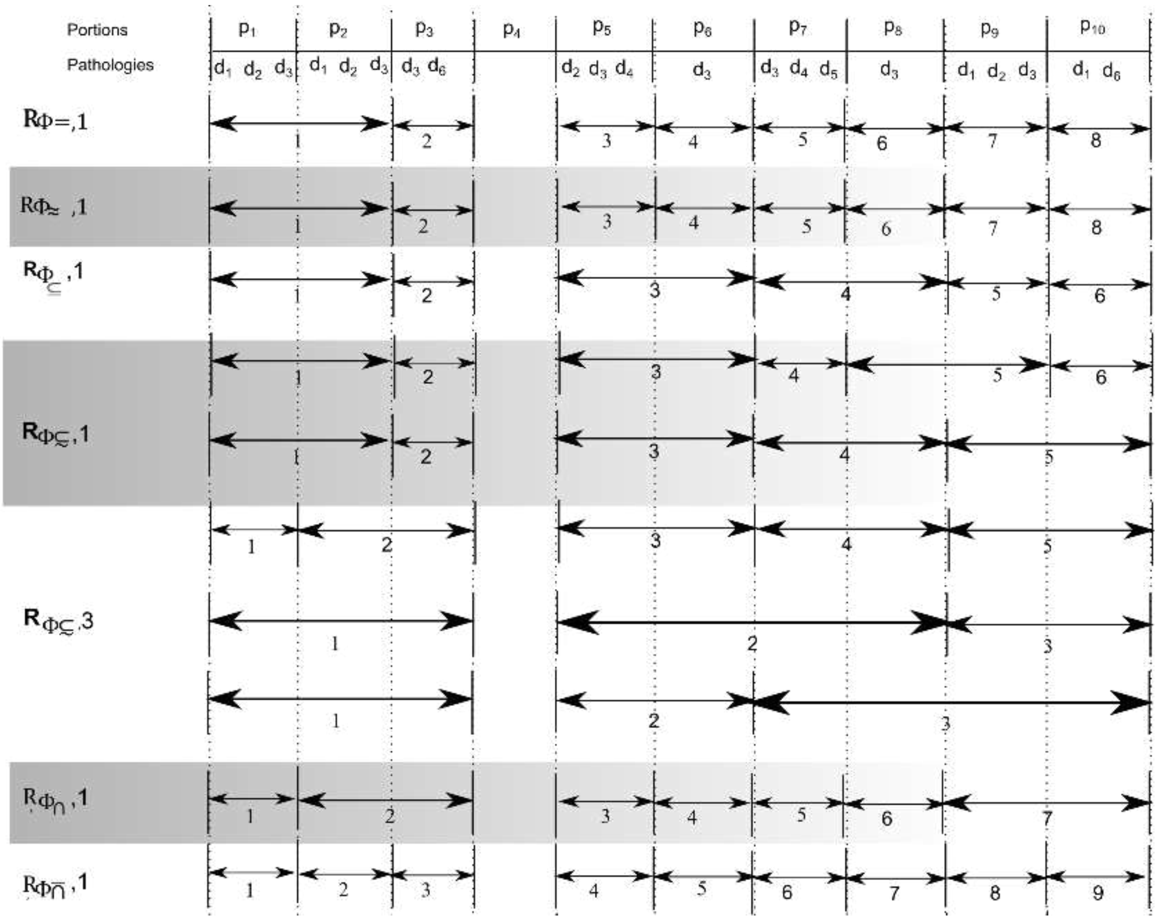


Fig. 11. Illustrative example with result of various selections of aggregation predicates and gap. Resultant ROIs are numbered and shown as aggregation of individual portions.

A different selection (last row, Fig. 11), by keeping $n=1$ but changing the predicate to R_{Φ_C} reduces the number of ROIs to one, i.e. $\{\{p_5, p_6, p_7, p_8\}\}$. Each portion in this ROI belongs to the Ground Degradation Pathology class from the PADTUN ontologies. The ontological representation of this portion is depicted in Fig. 10.

Finalising the Aggregation Function(s) to Implement. Experts were shown a mock-up of ROIs with different selections (above). The aggregation function *Portions with Approximately Equal Pathologies* (also known as *Portions with pathologies in the same family* (R_{Φ_F}) was deemed to be the most useful for decision-making and was implemented for the final version of the ROI inferencing service. The process of detecting regions with portions that have pathologies belonging to the same classification helps decision makers to decide on an overall approach they can take while addressing problematic tunnel regions. The grouping of affected regions according to the pathology classification is helpful in making decisions about expertise, treatment, and equipment required for maintenance. For example, infrastructure managers are required to send a different equipment to repair *lining degradation pathologies* from the one needed to fix *ground degradation pathologies*. Similarly, it will require different skillsets to repair different types of pathologies.

7 User Interface

PADTUN is a knowledge-driven intelligent system to support tunnel diagnosis decisions. The previous sections presented the intelligent components in PADTUN, namely the knowledge (captured and presented in an ontological model) and inferencing engine (including two parts — pathology inferencing and ROI inferencing). The inferencing algorithms presented in Sections 5 and 6 were developed as web services, which encapsulate intelligent features that can be invoked by any web-based interface. An example of such an interface is presented below (this is the prototype of the system instantiated for the French national railway company SNCF).

The web-based interface allows the system to be called on any device and at any location. Fig. 12 shows the main functionalities of the diagnosis system. Data with tunnel inspections can be uploaded in an xml format. The user can also remove tunnel data, if that data is no longer valid (or needed). Tunnel diagnosis decisions are supported by providing: (a) Regions Inferencing (an overview of the problem regions in the tunnel), (b) Pathologies Inferencing (an overview of the pathologies detected in the tunnel), and (c) a Pathology Dashboard (which allows in-depth inspection of each tunnel portion).

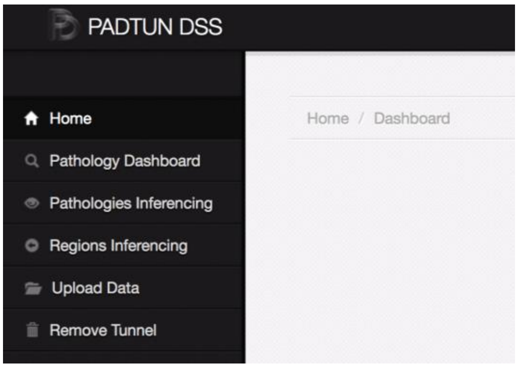


Fig. 12. The main menu of PADTUN.

Upload data. Domain experts at SNCF entered tunnel inspection data, including the disorders that have been recorded by surveyors and the influencing factors that provide relevant contextual parameters to be taken into account when diagnosing the tunnels. The data is collected in a tunnel inspection database, and uploaded in an xml format into PADTUN. The upload process automatically performs mapping of the database fields to the ontology concepts, storing the tunnel data in a triple store (see Section 3). The triple store is then accessed by the semantic services for pathology inferencing (see Section 5) and ROI inferencing (see Section 6).

Pathologies Inferencing. Tunnel inspection data is linked to the PADTUN ontologies which enables applying the knowledge to identify what pathologies may occur in tunnel portions. The pathology inferencing interface allows domain experts to get an overview of the pathologies detected in the tunnel, over all tunnel portions. This was the most often used interface by the domain experts at SNCF as it allowed them to see the overall condition of the tunnel, and to plan the repair work. An example output with pathologies inferencing overview is presented in Fig. 13. It can be seen at a glance that this specific tunnel has several ground degradation pathologies, specifically associated with weathering. The lining appears in a relatively good condition. Overall, there are areas that require urgent repair work (in the context of tunnel maintenance, urgency is measured in terms of years to allow proper planning of the maintenance work, e.g. in SNCF the most urgent planned repairs should take place within 6 years).

Fig. 13. Pathologies Inferencing interface in PADTUN: the tunnel is divided by portions of 10 meters which are numbered (column headings); for each portion pathologies are detected (main rectangle); and the overall urgency repair indicated (first row of the main rectangle).

Regions Inferencing. When planning tunnel maintenance work, tunnel experts want a high-level view of tunnel's condition indicating the areas where there is a spread of a particular family of pathologies. In PADTUN system, this functionality is achieved by calling the ROI inferencing service. An example of the regions inferencing interface is presented in Fig. 14. The tunnel shown has three regions of tunnel portions (note that SNCF define a tunnel portion to be 10 metres long) which have lining degradation spread: portions (1–4), (17–20) and (36–42). More critical is the condition of the ground — where an overall repair of the ground of the whole tunnel may be needed. This interface was particularly useful for tunnel experts because the regions indicated areas that required further inspection or allowed identifying what equipment would be needed for the maintenance. The tunnel experts could take a quick glance to grasp the overall situation of the tunnel and combine with the pathology inferences interface (see Fig. 13.) for a more detailed overview.

Pathology dashboard. The key advantage of using a knowledge-driven approach is the ability to provide full transparency of the system inferencing. This is provided with the Pathology Dashboard interface. This allows domain experts to inspect in detail the reasons for identifying specific pathologies for each of the tunnel portions. Fig. 15 illustrates the pathology dashboard interface. The user has selected a specific tunnel portion (Portion 1 in this case, i.e. the first 10 metres of this tunnel) and can see what pathologies are associated with this portion based on disorders (top window) and influencing factors (bottom window). The ranking takes into account whether a specific condition (disorder or influencing factor) is typical for a pathology, which means that it is likely to lead to the presence of that pathology. It also takes into account the number of disorders and influencing factors that have been associated with the pathology. In the example in Fig. 15, Carbonated Weathering and Freezing Thawing Cycles Degradation are the top ranked pathologies, because a typical disorder associated with these pathologies is present (Hollow sound) and another non-typical disorder is recorded (Moisture). If the influencing factors are taken into account, Rock Weathering is picked as the most likely pathology (top ranked) because there are two typical conditions that lead to this pathology (Hard conditions and Aggressive Water) together with two non-typical influencing factors (Medium fractured discontinuous density and Degradability).

The Pathology Dashboard (illustrated in Fig. 15) was particularly useful for in-depth analysis of the pathology inferencing which was used for evaluating PADTUN, as discussed in the next section.

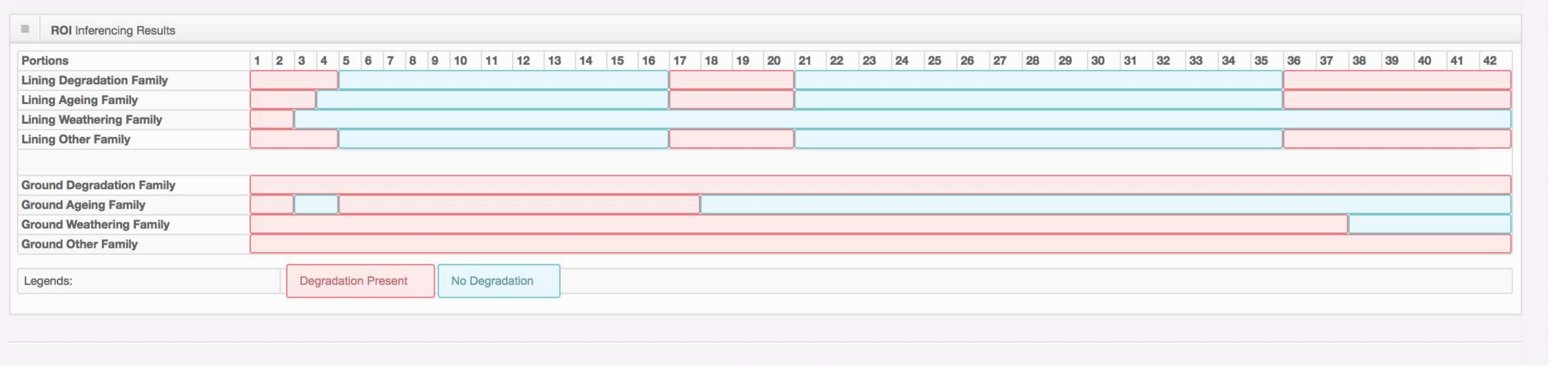
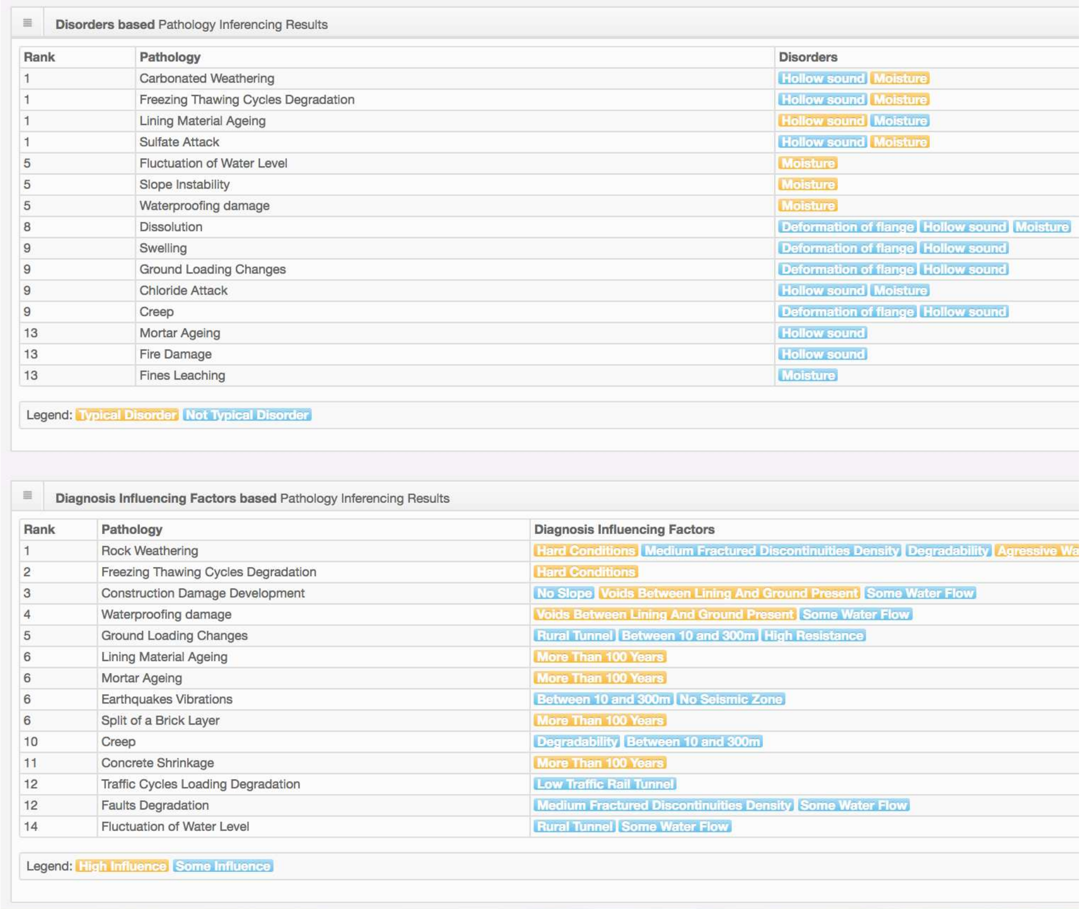


Fig. 14. Regions Inferencing interface in PADTUN showing the pathology stretch across tunnel portions. Red portions indicate the presence of pathologies such as Lining Degradation, Ageing, or Weathering.



Disorders based Pathology Inferencing Results

Rank	Pathology	Disorders
1	Carbonated Weathering	Hollow sound Moisture
1	Freezing Thawing Cycles Degradation	Hollow sound Moisture
1	Lining Material Ageing	Hollow sound Moisture
1	Sulfate Attack	Hollow sound Moisture
5	Fluctuation of Water Level	Moisture
5	Slope Instability	Moisture
5	Waterproofing damage	Moisture
8	Dissolution	Deformation of flange Hollow sound Moisture
9	Swelling	Deformation of flange Hollow sound
9	Ground Loading Changes	Deformation of flange Hollow sound
9	Chloride Attack	Hollow sound Moisture
9	Creep	Deformation of flange Hollow sound
13	Mortar Ageing	Hollow sound
13	Fire Damage	Hollow sound
13	Fines Leaching	Moisture

Legend: Typical Disorder Not Typical Disorder

Diagnosis Influencing Factors based Pathology Inferencing Results

Rank	Pathology	Diagnosis Influencing Factors
1	Rock Weathering	Hard Conditions Medium Fractured Discontinuities Density Degradability Agressive Wa
2	Freezing Thawing Cycles Degradation	Hard Conditions
3	Construction Damage Development	No Slope Voids Between Lining And Ground Present Some Water Flow
4	Waterproofing damage	Voids Between Lining And Ground Present Some Water Flow
5	Ground Loading Changes	Rural Tunnel Between 10 and 300m High Resistance
6	Lining Material Ageing	More Than 100 Years
6	Mortar Ageing	More Than 100 Years
6	Earthquakes Vibrations	Between 10 and 300m No Seismic Zone
6	Split of a Brick Layer	More Than 100 Years
10	Creep	Degradability Between 10 and 300m
11	Concrete Shrinkage	More Than 100 Years
12	Traffic Cycles Loading Degradation	Low Traffic Rail Tunnel
12	Faults Degradation	Medium Fractured Discontinuities Density Some Water Flow
14	Fluctuation of Water Level	Rural Tunnel Some Water Flow

Legend: High Influence Some Influence

Fig. 15. The PADTUN Pathology Dashboard interface. The user can select a tunnel portion and examine what pathologies are inferred based on the disorders recorded in this portion and the influencing factors.

8 Evaluation

8.1 Experimental Setup

Goal. An evaluation was carried out to validate the output of pathology inferencing, which allowed evaluating the ontology against its purpose (detecting tunnel pathologies). Furthermore, if pathologies are properly detected, the regions of interest (which identify the spread of pathologies) are also properly identified. Consequently, the prime goal of the evaluation was to find out whether the pathologies detected by PADTUN aligned with the pathologies detected by domain experts.

Tunnel data. For this evaluation, 46 tunnels (some 50 kilometres of tunnel portions) were selected by consulting tunnel experts at SNCF who suggested tunnel portions with a good variety of disorders and influencing factors. The tunnel conditions ranged from critical (repairs had already been planned) to safe (no action was required as there were no pathologies present, e.g. for relatively new tunnels). The selection also aimed to get a diversity of influencing factors. For example, the tunnels were with varied lining. Also, the tunnel age ranged from tunnels built in the last decade to old tunnels that had been bombed during the first and second world wars. Furthermore, the sample included tunnels with high and low passenger traffic.

In addition, an expert advisor from Swiss Rail provided the inspection data of one of their tunnels, together with the influencing factors for that tunnel. The data was entered in the SNCF tunnel inspection database, and stored in the xml format that is required for PADTUN. The tunnel data was then uploaded in PADTUN, and the output was inspected by the experts using the interface shown in Section 7.

Tunnel experts. The evaluation was conducted with tunnel experts from the project with extensive experience in diagnosing tunnels and strategic decision-making about tunnel maintenance in transportation. It included three experts at SNCF and one expert at Swiss Rail.

Procedure. The experts were provided with the output of the pathologies inferencing (see interface shown in Fig. 13). During initial discussions with the experts, it became evident that although they agreed with the individual inferencing (disorder or influencing factor based) they were not satisfied with the cumulative calculations (pathology inferencing interface). We discovered that the pathologies were correctly calculated based on disorders and diagnosis influencing factors and according to the rules encoded. However, experts always expected a pathology to be present in both lists for them to consider the pathology in the cumulative list. As a result of this exercise, this cumulative list rule was added to the ontology and to the pathology dashboard. Subsequently, the cumulative pathologies list for each tunnel portion was shown to the experts. Two tunnel experts from SNCF were asked to assess independently the pathologies identified in each individual tunnel portion. They had to indicate **false positive cases** when a pathology was identified wrongly (i.e. the experts thought that the pathology was not present but the system identified that the pathology was present) and **false negative cases** when a pathology was missed (i.e. the experts thought that the pathology was present but the system had not identified this pathology for the specific portion).

A discussion between both experts, together with the other expert at SNCF and the expert from Swiss Rail identified common diagnosis conventions (which allowed aggregating the outputs from both experts). The results were then discussed, looking specifically at the false positive and false negative pathology detection cases.

8.2 Results

The pathology evaluation method followed a binary classifier evaluation, where an individual pathology acts as a class. As a gold standard, we work with the domain experts to identify correct or incorrect responses obtained from the PADTUN pathology inferencing system. Experts could perform these analysis on the web interface or export spreadsheets. Fig. 16 illustrates how the gold standard was obtained, showing an example from a single tunnel annotated by an SNCF expert. The expert has annotated the incorrectly predicted pathologies as ‘XP’ (in classification terminology, these are the false positive (fp) which have been marked in green boundary). The expert also adds red coloured ‘P’ where PADTUN misses to indicate the pathology presence (these are the false negative (fn) which are highlighted with a blue boundary). There are cases where the expert agrees with the pathologies PADTUN has identifies (these are the true positives (tp) where the expert makes no correction on the

PADTUN outcome). Similarly, where the expert agrees with PADTUN on pathology absence (this is a true negative (tn) case), the empty cells in the spreadsheet are unchanged by the expert.

We use three evaluation measures: accuracy, positive predictive value (PPV), and negative predictive value (NPV). Accuracy is the ratio of pathologies correctly inferred by the system over all tunnel portions; accuracy is defined as: *(tp+tn)/(tp+tn+fp+fn)*. PPV is the ratio of predicted pathologies, or class presence, which are in agreement with the domain expert over all predicted pathologies; PPV is defined as: *tp/(tp+fp)*. NPV is the ratio of predicted pathology absences, or class absences, which are in agreement with the domain expert over all class absences; NPV is defined as: *tn/(tn+fn)*. We examine these evaluation measures with different cut-offs in the PADTUN rankings. Our domain experts have identified two cut-offs: 3 and 5 (i.e. top 3 or top 5 pathologies recommended by PADTUN). The cut-off for ranked disorders and influencing factors affects the final pathology decision as only those disorders and influencing factors above the cut-off are considered. This parameter was requested by our domain experts.

Table 2. Evaluation of the Pathology finder's inferences. We evaluated on the two cut-offs as proposed by the domain experts – top 3 recommended pathologies or top 5 recommended pathologies.

	PADTUN Cut-off 3	**PADTUN Cut-off 5**
Accuracy	0.93	0.95
PPV	0.70	0.68
NPV	0.96	1.0

Table 2 shows the results of evaluation metrics calculated using PADTUN outputs. We obtain slightly better accuracies when PADTUN suggested the 5 most likely pathologies for each tunnel portion. Between the domain expert selection of cut-off 3 and 5 as system parameters: the latter includes more influencing factors and disorders for the final pathology inference. For cut-off 5: we obtain 95% accurate results with perfect negative predictive value (NPV). PADTUN's positive predictive value is rather low (i.e. the system detects more false positives). However, this is by design to ensure the system err on the side of caution. For our application, a missed detection of a pathology (i.e. existence of false negatives which lowers the negative predictive value) is seen as the most critical error.

To get deeper insight into the accuracy metrics, we visualise the metrics for each pathology and tunnel.

Fig. 17 shows the accuracy trends, visualized for all tunnels and pathologies. PADTUN performs well for most of the pathologies for all tunnels. However, there are some pathologies which are consistently wrong for most of the tunnels. There are three such pathologies, namely: creep, ground loading changes, and waterproofing damage; corresponding to the accuracy threshold of 0.95.

Fig. 18 shows the positive predictive values for all pathologies and tunnels. It can be observed that three pathologies, also identified earlier, are wrong for most of the tunnels. For these three pathologies PADTUN is not confident, decides to err on the side of caution, and tends to mark everything as erroneous or pathological. The negative predictive values analysis for individual pathologies and tunnels is shown in Fig. 19. The negative predictions are correct, most of the time, i.e. PADTUN indicates the absence of pathologies which is the most important in our decision support context.

As shown in in Fig. 20, the pathologies that were missed by PADTUN have also a relatively low prevalence (the number of positive conditions or the pathology presence in gold standard divided by the total data population or the tunnel portions), i.e. these are relatively rare pathology occurrences. Having the knowledge rules available to experts enables scrutinising the system's inference process and identifying the reasons for missing pathology detection. A closer expert examination of the three pathologies for which PADTUN produced false negatives indicated the need to tune the corresponding pathology rules which included more constraints leading to missing pathologies.

Fig. 17. PADTUN accuracy for each pathology (shown in rows) and each tunnel (shown in columns). Darker red colours indicate a higher error score.

Fig. 18. PADTUN positive predictive value for each pathology and each tunnel. Darker red colours indicate a higher error score.

Fig. 19. PADTUN negative predictive value for each pathology (shown in rows) and each tunnel (shown in columns). Darker red colours indicate a higher error score.

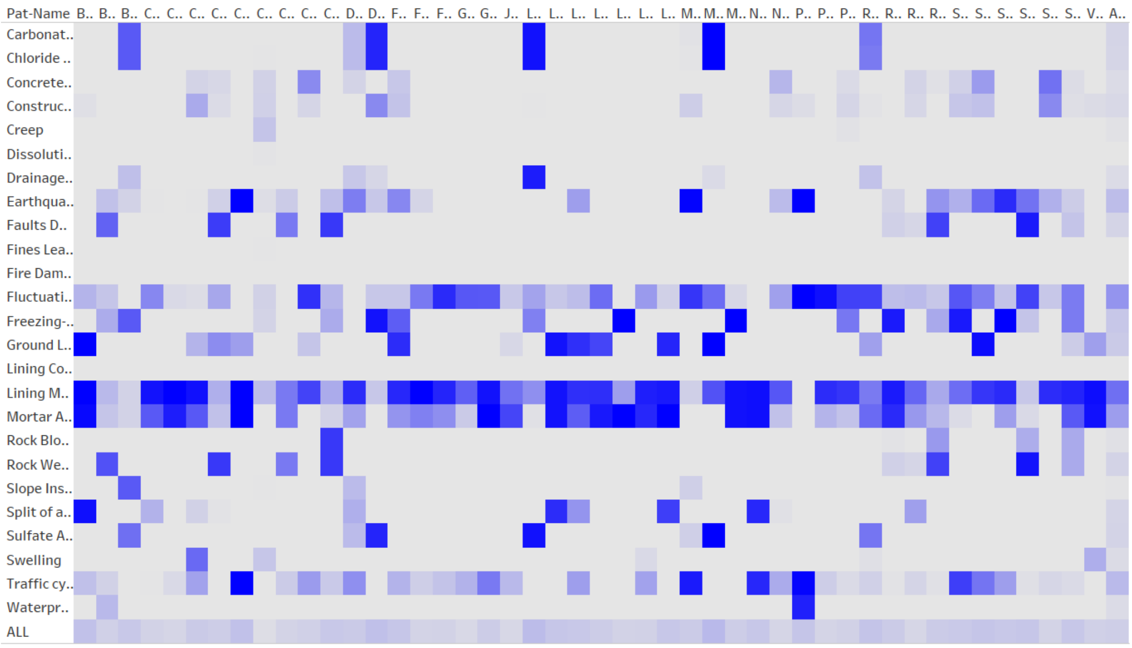


Fig. 20. Prevalence for each pathology and each tunnel. Brighter blue colours indicate higher occurrence. The prevalence for classes with higher errors is low. Thus, our metrics are not influenced by extreme cases.

9 Discussion and Conclusions

Summary. Tunnel assessment requires complex decision making to ensure full safety while optimising the maintenance and repair costs. This involves regular pathology diagnosis which is complicated by a range of factors, such as infrastructure ageing, climate change, and rapidly increasing urbanisation. Tunnel maintenance in general, and pathology diagnosis decisions specifically, are taken by experienced experts who often apply their tacit knowledge. This can result in subjectivity and poor scalability of decision processes that have high societal and economic impact. The paper presents how such challenges have been addressed by an interdisciplinary team of tunnel experts and knowledge engineers within the European project NeTTUN. This led to the development of PADTUN — an intelligent decision support system that assists with pathology diagnosis and assessment of tunnels using observed tunnel disorders and influencing factors. PADTUN utilises semantic web technologies for knowledge capture, representation, and reasoning:

- The PADTUN ontologies, which are represented in the internationally established Web Ontology Language (OWL) standard, provide the first ontological model that captures the engineering experts' decision process concerning the maintenance of tunnels. The ontological model (which includes 125 concepts, 49 relations, 590 individuals, and 3981 axioms) was provided by domain experts at the French railway company SNCF, further extended by following tunnel maintenance guides and international standards, and validated by a domain expert from Swiss Rail.

- Existing tunnel inspection data has been linked to the PADTUN ontologies which enables the use of ontology reasoning to diagnose pathologies from recorded tunnel disorders and influencing factors. Our reasoning mechanisms also identifies extended tunnel regions where pathology families spread to facilitate planning of repair actions.

PADTUN was evaluated on a database of 46 SNCF tunnels (some 50 kilometres of tunnels), and also an example tunnel from Swiss Rail. The system performed well with regard to false negatives (i.e. cases when the system erroneously misses pathologies) which is the most important metric in this decision context. There were only 3% false negatives, which concerned rare occurrences of few pathologies that were generally hard to identify (as pointed out by our domain experts). Nevertheless, the experts in the evaluation study stressed that some pathology misses (e.g. Rock block instability) could be fatal, and suggested ways to change the ontological model to ensure these pathologies would be properly detected. The cases of false positives (pathologies that were not present but were identified by the system) were treated as less worrying by the experts in our evaluation — in critical decision making contexts, it is preferred that the initial diagnosis indicates any possible pathologies which trigger further tunnel inspections and analysis. One specific false positive case that needed fixing was the pathology Creep. Using the PADTUN pathology dashboard, the experts carefully inspected tunnel portions where this pathology was suggested and could check the system's rationale for its suggestions (this of course is one of the advantages of symbolic reasoning such as ontology based reasoning). This allowed the research team to identify that the constraint of overburden was missed in the ontology. To address this with the modelling conventions followed in the ontology, it was necessary to define two separate concepts for Creep – one representing the occurrence within the tunnel (and is treated as pathology that needs attention) and one associated with the ends of the tunnel (when the occurrence is expected and is not seen as pathology).

Generality and broad applicability. PADTUN utilises state-of-the art semantic web technologies and has been tailored for the needs of tunnelling and transportation inspectors and managers. In addition to the novel ontological model and intelligent decision support system, a key contribution of our work is the methodology we have developed for engaging with engineering experts who have extensive domain expertise but do not have a knowledge engineering background. The paper describes how we have taken this into account by providing a systematic way to engage with engineering experts, such as (a) following an iterative design with interim evaluations, including a series of interdisciplinary workshops to identify the core concepts and relationships in the domain, (b) agreeing early on the ontology scope and purpose, (c) using concept maps and spread sheets to facilitate the modelling process, (d) linking ontology with real world data, and (e) evaluating fitness for purpose with selected real world cases. Furthermore, the methodology includes modelling conventions to capture the key concepts and relationships in the domain, considering both simplicity (to ensure we do not overburden domain experts) and generality (to ensure the ontology is applicable in a range of cases, not just the examples considered in the examples). This has led to identifying the core elements related to pathology diagnosis from observable tunnel data, which can be applied beyond the tunnel diagnosis domain. Both the ontology engineering methodology and the core modelling components are rather generic and have been adopted by us in several other intelligent decision support systems in engineering domains with high societal importance, e.g. supporting construction companies and local authorities in sustainable street works planning and management (Wei et al., 2018) and supporting businesses in Circularity decisions (Mboli et al.). We are currently adapting the ontological approach for fault analysis and system safety in defence scenarios.

Further deterioration and repair work planning. Pathology detection is a crucial aspect in infrastructure assessment which triggers decision processes to plan repair work. For this, the level of deterioration and urgency of repair are crucial. While domain experts could identify factors that would be catalysts for further deterioration (e.g. tunnel age, geology, past accidents), it became clear that the combinations of factors affecting the urgency of repair decisions were not feasible to capture in an ontological model. Taking advantage of the availability of a reasonable size of data (considering tunnel portions as the main data units and including all past inspections), as well as the availability of experts to provide ground truth for urgency of repair, we derived machine learning models for predicting urgency of repair. The reader is directed to Gatsoulis et al. (2016) for detail of this strand of our work. Several classification models were evaluated. Good performance was achieved with a random forest model, while a decision tree model provided comparable performance and at the same time allowed clarification when the domain experts demanded explanation of the model predictions.

Data availability. In the digital era, a plethora of data about infrastructure conditions is becoming available. However, having a dataset sufficient to enable data-driven decision support for critical cases, such as tunnel diagnosis and maintenance, is still a major challenge. For example, although the tunnel inspection data available to our research team was of a reasonable size for ontology validation (as presented in Section 8) and for urgency repair (as presented in Gatsoulis et al., 2016), it is not large enough for training machine learning models for pathology detection, especially for the difficult cases with rare pathologies whose misses can be fatal (e.g. Rock block instability). Moreover, as tunnels are inspected every 6 years and digital data has been collected only in the last 10–15 years, the temporal data available to us was quite limited (we had 2–3 inspections per tunnel) which does not allow more sophisticated deterioration modelling (yet).

Combining knowledge representation and machine learning. Involving domain experts who provide the tacit knowledge needed in the decision process is paramount, especially in high impact decision contexts as the one presented in this paper. Indeed, most of the practical applications of semantic technologies adopt top-down approaches that primarily rely on the knowledge, intuition and insights of experts in the field (Kirrane et al., 2019). Expert availability was a key advantage for the project we presented here (involving highly experienced tunnel experts from the French and Swiss railways). However, in many cases domain experts may not be available or may not be able to dedicate sufficient time to the research. Mixed methods approaches that combine knowledge representation and machine learning are starting to emerge (Kirrane et al., 2019). For example, data might allow the ontology in general or the inferencing system in particular, to be automatically updated, based on data generated by the surveyors and also based on the feedback of the tunnel and transport managers. Combining knowledge-based and machine-learning-based techniques can allow not only adapting to the dynamic tunnel and transportation environments, but also the ability to explain the reasoning behind the diagnostic decisions as a tunnelling or transportation expert would.

The biggest advantage of knowledge-driven approaches, such as the one presented in this paper, is the ability to provide meaningful exploration and justification of the suggestions by the intelligent system, as the model used is similar to the experts' way of conceptualising the domain. In addition to assisting with tunnel diagnosis and maintenance, PADTUN was also reported by our collaborators at SNCF to be useful for (a) training less experienced tunnel engineers, as it stores the tacit knowledge and experience of tunnel experts, and (b) preserving the tacit (intuitive) knowledge of experienced tunnel experts who may retire (as it indeed happened during the course of the NeTTUN project).

CRediT authorship contribution statement

Vania Dimitrova: Conceptualisation, Methodology, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Muhammad Owais**

Mehmood: Conceptualisation, Methodology, Investigation, Visualisation, Writing - original draft, Formal analysis, Data curation. **Dhavalkumar Thakker:** Conceptualisation, Methodology, Investigation, Visualisation, Writing - original draft, Software. **Bastien Sage-Vallier:** Validation, Resources. **Joaquin Valdes:** Conceptualisation, Methodology, Validation, Resources, Project administration, Funding acquisition. **Anthony G. Cohn:** Conceptualisation, Methodology, Investigation, Writing - review & editing, Project administration, Funding acquisition.

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