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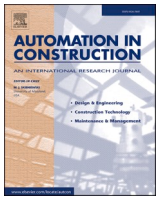

From surveys to simulations: Integrating Notre-Dame de Paris' buttressing system diagnosis with knowledge graphs

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ABSTRACT

The assessment of structural safety and a thorough understanding of buildings' structural behavior are critical to enhancing the resilience of the built environment. Cultural Heritage (CH) buildings present unique diagnosis challenges due to their diverse designs and construction techniques, often requiring attention during maintenance or disaster relief efforts. However, collaboration across CH and Architecture, Engineering, and Construction (AEC) fields is hindered by increasing information complexity and prolonged feedback loops. This paper introduces a methodological approach utilizing Knowledge Graph technologies to integrate structural diagnosis information and processes. The approach is applied to the diagnosis of the Notre-Dame de Paris buttressing system, demonstrated through a proof-of-concept knowledge system. By leveraging Knowledge Graph functionalities, insights are derived from the spatialization and provenance of mechanical phenomena, including observed or simulation-predicted cracks in mortar-bound masonry.

1. Introduction

In the context of Cultural Heritage (CH) buildings and infrastructures, the conservation and restoration activities have as a common endeavor to ensure that built assets last over time, along with their cultural and socio-economic values. From the broader perspective of Architecture, Engineering and Construction (AEC), such works are as many edge cases which cast a light on the current craftsmanship and industry practices. This is due to their uniqueness in design or remarkability in the achievement of their construction, drawn from the architectural and structural expressiveness of the material. Stonework renders iconic structural components, integrated as a coherent whole while varying scale and, occasionally, construction time. As a prime illustration for this material mastery, the Gothic style features great light-filled volumes, enclosed by slender structures, that provides reference for tracing the evolution of stonework, then stereotomy, over centuries (Fig. 1). Their apparent sturdiness conceals maintenance efforts and recovery from disasters, delivered within the conservation-restoration activities during the building life cycle. Given the prevailing doctrines on cultural heritage preservation, the maintenance phase of these structures is envisaged as enduring. It is a renewed challenge to both accompany their mutations of social function, of usage, and to build their resilience to threats and natural deterioration [1].

Effective decision-making during the maintenance phase and pertinent design choices originate from a comprehensive understanding of the built asset's current condition. This requires an interdisciplinary approach encompassing conservation surveys, heritage value assessments, material identification, and more. Among them, structural diagnosis specifically aims to evaluate service capacities and safety margins, explain observed damage, and provide "a full understanding of the structural behavior and material characteristics [that] is essential for any conservation and restoration project" [2]. Since precise representation of real phenomena featured on the CH asset is challenging, reliable insights are derived from a combination of observational, analytical, and interpretative methods [3] such as damage inspection, mechanical simulation or mechanical testing. These pertain to the civil engineering field and are refined provided with cross-pollination with other studies.

Post-disaster relief highlights the critical role of diagnoses in the maintenance phase. The April 2019 fire at Notre-Dame de Paris cathedral is no exception. The burnt framework and severely damaged vaults immediately question the stability of the entire structural system (Fig. 1.

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a). Recovery efforts involved in an unprecedented collaboration [4], performing multi-scale diagnoses [5], non-destructive mechanical testing [6], instrumentation of upper parts, and multi-physical simulation campaigns.

Both routine and disaster-relief diagnoses are data- and knowledge-intensive. A successful interdisciplinary approach relies on aligned data products and meaningful resources to share insights, explore alternatives, and curate traceable hypotheses. Yet, crippling information gaps hinder their integration and accessibility during the CH building lifecycle:

- incompleteness: only partial building information reached us through history, nor is potentially identifiable via modern techniques.
- heterogeneity: uneven quality and granularity in the data sets.
- information attrition: data quality decreases as it is exchanged.
- rarefication of raw data: synthetic documentation is maintained and exchanged between diagnostic activities, but raw survey data or provenance assessments are seldom included.

These gaps are fueled by technical incompatibilities, cultural barriers, communication silos, and the inevitable turnover of experts throughout the endless life of the building. Not only it obscures crucial information, italso silences valuable feedback loops. Still, the challenge is "to find ways to allow those communities to collaborate effectively with one another whilst maintaining their existing, efficient, effective separate world views" [7].

1.1. Knowledge graphs for sharing masonry CH buildings diagnosis information

This article presents an experiment of using a Knowledge Graph for sharing, visualizing and reusing the body of knowledge constituted from the structural diagnosis of a heritage building. It aims to bridge civil engineering with the conservation-restoration communities using a semantic framework.

Therefore, the related research question is one of integration of heterogeneous, spatialized, uncertain data: *How can we effectively integrate structural diagnosis information of Cultural Heritage masonry assets in a structured way, allowing common understanding and interrelations between the disciplines involved?*

More specifically, we want to narrow this question to the interoperability between visual inspection data and mechanical simulation results: *How can we effectively provide a two-way link relating the study of an alteration observed on the physical material, to the multiple modeled and predicted damage quantified through mechanical simulations?*

We favor graph-based structuration of knowledge for (i) its conciseness in a setting characterized as complex (Section 3.1); (ii) its capacity to retrieve both local and global information, from the metadata of a resource to the inferences across resources; (iii) flexibility in the modeling strategies, to shift from document-centric to resource-centric archiving strategy (Section 3.2). Our work demonstrates that interoperability of rich AEC and CH data products, such as those detailing degradation phenomena, benefit from being established at the knowledge level. Therefore, the two-way exchange of qualitative and quantitative data between the aforementioned communities is channeled throughout the use of a Semantic Web based Knowledge Graph.

We explore Knowledge Graph design and construction from two perspectives. First, we focus on knowledge modeling tailored to the domain, robustly describing the provenance of degradation phenomena as spatial resources. Second, we design a knowledge system that hosts the Knowledge Graph, enriching and processing data for both human readability and machine actionability. Respectively, we adopt Methontology [8] and eXtreme Design [9] for pattern-based reuse of the standard CH ontology CIDOC CRM [10]. We follow the design science guidelines to design, implement and validate the knowledge system as an artifact [11]. Our approach is evaluated by integrating structural diagnosis data from Notre-Dame de Paris's buttressing system to assess its effectiveness.

1.2. Overview of the outline of the article and the main contributions

In this article, we first give a brief overview of the state of the art (Section 2) in performing structural diagnosis of cultural heritage masonry buildings (Section 2.1) and using Knowledge Graphs to structure the corresponding data produced by the AEC and CH experts (Section 2.2). More precisely, we refer to the use of Semantic Web technologies for the design and management of a Knowledge Graph (Section 2.2.1), followed by the application of knowledge graphs in the AEC and CH field (Section 2.2.2). In Section 3, we expose the methodological framework we employ to design the ontology and the knowledge system framework. From the the requirements and competency questions capture (Section 3.1.), we outline the use of Ontological Design Patterns (ODP) for extending the scope of the CIDOC CRM ontology to the structural diagnosis of building (Section 3.2). By ODP, we refer to small ontological patterns used as building-blocks for modeling a knowledge domain. Finally, we detail the integration of the Knowledge Graph within an event-driven information system (Section 3.3). In Section 4, we demonstrate the use of the Knowledge Graph for bridging the observational data on a building, cartographied on an annotated point cloud, with mechanical simulation results produced with the Discrete Element Method. We begin with a step-by-step application of the eXtreme Design

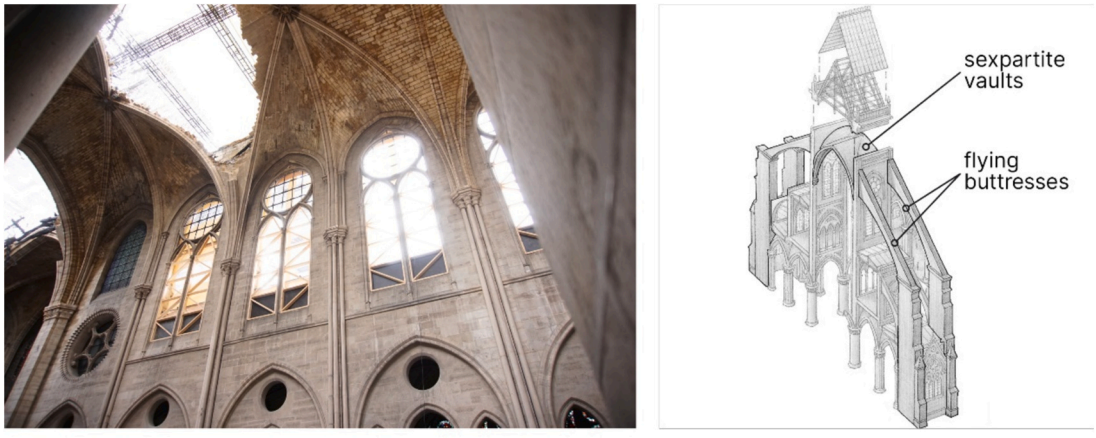

Fig. 1. (a) April 2019 fire damage to Notre-Dame de Paris' nave and transept vaults (@Bestrema); (b) Notre-Dame choir's sexpartite vault and buttressing system.

methodology to design a basic ODP (Section 4.1) underlining the reuse of existing thesaurus and metadata vocabularies. By metadata vocabulary, we refer to structured list of property built for interoperability. We move forward to demonstrate the linking of building alteration data from the perspective of spatial information (Section 4.2) and the provenance of collected data with reference to the diagnostic activity and its dependencies (Section 4.3). The result section includes a proof of concept of the proposed framework, evaluated with the integration of structural diagnosis data from Notre-Dame de Paris's buttressing system. Finally, the study concludes with insights and future research directions (Section 5).

2. State of the art

In this section, we present a summary over the structural diagnosis of masonry CH buildings (Section 2.1), and the role of Knowledge Graphs in organizing data from AEC and CH fields (Section 2.2). Thus, we first describe the data and domain knowledge to integrate, then a way of structuring them as graphs.

2.1. Structural diagnosis for the conservation of masonry CH buildings

Structural diagnosis aims to specify the stability, the integrity of the parts, the performance of the structure, of a building or an infrastructure. Due to the unique nature of CH buildings, their structural diagnosis benefits from the interplay of observational, analytical, and interpretative studies [3]. These studies rely heavily on accumulated expertise to identify typologies and draw analogies among the existing works, their parts and their key features.

The tasks related to structural diagnosis investigate structural behavior and damage, building usage and social function, material characteristics such as mechanical, physical, chemical, and the kinds of its decay. They account for both the present and the historic condition of the asset, then lead to uncover the causality that tie the degradation phenomena. Due to the uncertainties of the as-built context, there is an interplay between these tasks and other studies conducted on the asset, in particular condition assessment, heritage value assessment and historical studies. As an illustration, historical studies can provide century-old clues about usage, design, restoration or constructive techniques choices that impact the actual structure. Embracing operational and scientific endeavors, these interrelated activities share common attributes:

- they are systematic in their methodology to ensure information consistency and reliability.
- they rely on accumulated knowledge within its disciplinary spectrum.
- they require interdisciplinary collaboration with the synergistic expertise of engineers, architects, conservators, and diagnosticians.
- they operate on asynchronous time frames while remaining interdependent in terms of task-flow and information flow.

Current structural diagnosis methods are incremental. The information and generated data feed into a common body of knowledge about the asset until a consensus is reached on its actual structural condition and performance. It can stop at any step depending on the case's complexity. The first step involves general documentation of the structure (e.g. function, location, topography) and is followed by preliminary surveys of the geometry, materials and damage. They are recorded on reports, annotations of 2D drawings, orthophotos [5], or 3D point clouds [12,13] produced by state of the art photogrammetry or lidar surveying techniques. The next step includes specific surveys, the most common of which relate to material characterization and internal composition identification. In the CH context, non-destructive techniques such as sound velocity measurements for the characterization of mechanical properties, or ground penetrating radar for internal composition cartography are preferred over sampling and testing [3,14]. Finally, a last stage triggers in situ instrumentation if the detailed analysis of a temporal phenomenon is needed [15], or mechanical simulation to clarify the structure's behavior and internal distribution of forces.

Both the building type and its construction material frame the design of diagnosis activities. For masonry buildings, massiveness and ductility are the prominent features of these structures. At the material level, the stone masonry bonded with mortar offers a high resistance to compression but a quasi brittle response to tension and shear [16]. These characteristics drive the design of the structural components: due to the material performance in compressive strength, the stability of a masonry structure is built from the efficient routing of thrusts across the structural components down to the foundations, in order to avoid tension and shear in the material. In circumstances of tension and shear, these mechanical stresses immediately lead to cracks in the masonry, geometric deformations and rotation of blocks within the masonry panels of the structural components [16]. Ultimately, these flaws in the structural components can lead to collapse mechanisms global to the structure. Therefore, diagnosis activities give careful attention to identifying deformations and cracking patterns that may reflect a compromised structural integrity and stability [17].

Likewise, the construction material frames the expertise, techniques and models used in diagnosis activities. For mechanical simulation and modeling, the goal is to depict the structural condition of a building given its material, its geometry, its history and a simulation scenario. In order to accurately replicate the structure response to mechanical loads and stresses, the simulation models have several dependencies: (a) a material model, to describe the characteristics of a material by its constitutive laws; (b) a geometric model, to represent the volumes of the structural components; (c) the boundary conditions, to represent the loads and stresses applied to the structure according to a simulation scenario (d) an initial state serving as a starting point for the scenario. In the case of stone masonry bounded by mortar, several modeling strategies coexists to represent the behavior of masonry structures with varying granularity (Fig. 2) [18]. For instance, Continuous Homogenized Material (CHM) strategies trade the simplification of the geometric model, considering only the shape of the structural component as a meshed envelope, with the complexification of the material model, now responsible to replicate the anisotropy and heterogeneous composition of the masonry. In contrast, the Discrete Element Method (DEM) among the Block-Based Models (BBM) strategies relies on the complex geometric modeling of the masonry apparel, as it solves the blocks dynamics taking into account interactions at their interfaces [19,20], while it keeps the material modeling simpler.

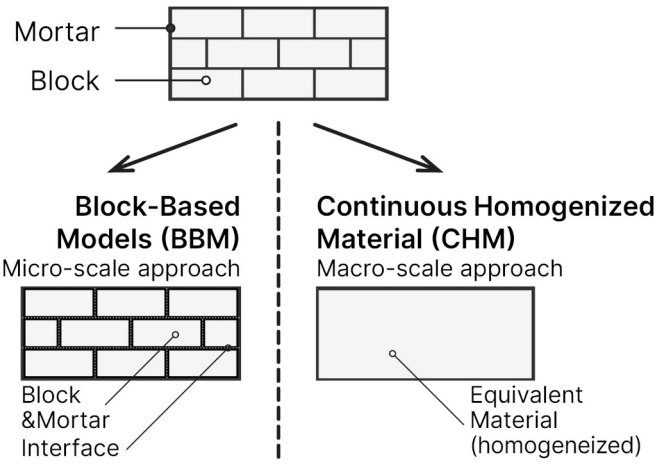

Fig. 2. Block-Based Models (BBM) and Continuous Homogenized Material (CHM), two strategies for modeling masonry-based structures.

The effective use of mechanical simulation in diagnosis relies on constructing accurate simulation scenarios, each reflecting a hypothesis about the structure's loading history. A hypothesis is validated by matching observed mechanical features, such as crack patterns or deformation, with simulated outcomes. Once a scenario is validated, the simulation model can be used to support diagnostic tasks in other disciplines, predict the performance of conservation-restoration design solutions or to monitor the physical asset with a synchronized digital model [21].

From the process perspective, such insights come with the cost of computing time and highly specific expertise for the design, analysis and interpretation of the simulation model. From the data perspective, they come with the cost of the lack of support for managing and recording both the simulation results and its dependencies. Hence, the evaluation of a simulation scenario is mostly a manual process, mapping the observed flaws on the building and the parameters values within the simulation results.

2.2. Graph-based management of data

Graphs provide "a concise and intuitive abstraction" to integrate, manage, and derive value from domain-specific data [22]. Nodes in the graph represent tangible and intangible entities within the knowledge domain, while edges depict their relations, whether hierarchical or cyclical. Information retrieval in graphs efficiently traverses scales and layers of information as it can be local, global or pattern based. This accounts for their ability to encapsulate heterogeneous interconnected data and provide both specific and global perspectives [23].

A Knowledge Graph is defined as a "data graph potentially enhanced with representation of schema, identity, context, ontologies and/or rules" [22]. In mathematical terms, data graphs typically take the form of a property graph or a directed edge-labelled graph in order to structure data. A property graph "allows a set of property-value pairs and a label to be associated with both nodes and edges" [22]. And directed edge-labelled graph are constituted by the connection of a set of nodes with a set of labelled edges. As an enrichment of a data graph, a Knowledge Graph may combine at least one feature from (i) a metamodel describing the possible entities and relations in the domain, (ii) a persistent identification passed by the node or an edge, (iii) a manageable scope of truth for the dataset or (iv) formalized knowledge for information entailment. The combination of those features supports domain disambiguation, enhances the expressivity of the knowledge base, and lets new information be entailed via formal deductive reasoning. Following this definition, the knowledge addressed within these graphs is explicit knowledge [24].

2.2.1. Semantic web technologies for knowledge graphs

Knowledge Graph design and application is one of the driving themes for the Semantic Web [25]. In the last decades, Semantic Web technologies have been enhanced to provide a set of efficient tools and methods aimed at data sharing, discovery, openness, integration, and reuse. Knowledge Graph development is tied with Semantic Web endeavors, tinting the development of Linked Open Data with industry-specific requirements [23].

Semantic Web interfaces Description Logics from a modular stack of languages to provide a rich development environment for structuring a knowledge base as a graph. These knowledge bases are defined by interlinked sets of axioms for making claims about recorded facts. The Terminology Box (TBox) and Assertional Box (ABox) are two sets central to the representation of knowledge, with the TBox containing axioms that defines a knowledge domain concepts and properties, while the ABox holds specific facts about individuals linked to the TBox axioms. Together, these statements constitute the foundation of a Knowledge Graph [22,26]. Therefore, the Semantic Web stack provides the RDF (Resource Description Framework) as a basic syntax for expressing statements and structuring them in directed edge-labelled graphs [27]. RDF Schema (RDFS) offer a semantic extension of RDF as a "data-modelling vocabulary for RDF data" [28] applicable for expressing axioms consistent with ABox and TBox sets. Web Ontology Language (OWL) and RDFS both offer a concise way to encapsulate knowledge by representing concepts and their relationships in an ontology.

Ontologies are defined as "formal, explicit specification of a shared conceptualization" [29], and known as a "main vehicle for data integration, sharing, and discovery" [25]. They orient the modeling of graph data during the update of the knowledge base with new facts and individuals. The set of TBox axioms they gather for modeling the knowledge of a domain can be reused across distinct knowledge bases, thus making their datasets instantly interoperable. Finally, deductive knowledge can be derived from the facts and axioms recorded in the knowledge base through the various entailment regimes the reasoners algorithms can provide [22]. These features encourage ontology reuse for structuring data or for extanding the scope of an existing model for relevant applications (Section 3.2).

In addition to languages for defining knowledge graph statements, the Semantic Web stack includes tools for entity disambiguation and internal coherence verification. Each individual is identified using an Internationalized Resource Identifier (IRI) [27], while Shape Constraint Language (SHACL) allows for validation of RDF graph data against "shape graphs", which are patterns used to assess the coherence of the graph relative to a schema [30].

Considering the array of sources and expertise from AEC and CH processes thoughout a building asset's lifecycle, Knowledge Graphs offer promising prospects for data integration and organization. Supported by the Semantic Web's framework, it facilitates the percolation of communities across domains and the persistence of datasets.

2.2.2. Knowledge graphs and data integration in AEC and CH fields

Knowledge management and integration of AEC and CH data have emerged as vibrant domains in recent decades. In line with the scientific literature on general building information management, most of the publications pertaining to the diagnostics and maintenance of built works are shaped by Built Information Modeling (BIM) or Digital Twin (DT) paradigms. Knowledge Graphs enrich BIM and DT by facilitating information structuring, enabling knowledge-based processing, and supporting explicit and implicit derivation of valuable insights from existing data on the built environment [31]. The sole constraint of the DT on information is to enable a two-way real-time retroaction from the physical object to its digital model [21]. Whereas BIM addresses the representation and exchange of structured building information, often emphasizing 3D modeling as a core aspect of its approach [32]. The open ISO standard, Industry Foundation Classes (IFC), is proposed to streamline information sharing for "[facilitating] design, construction and operation processes to form a reliable basis for decisions" [33]. Academic efforts successfully brought the IFC schema, originally modeled with EXPRESS modeling language and inherited from STEP specification, to Semantic Web RDF and OWL formalizations [34] as a standard serialization of the model. This is in keeping with the bolstering of IFC schema through various extensions, to enhance information granularity of this high-level schema. Therefore, several initiatives address entailments on building topology [35], description of monitoring information [36], bridging with standard ontologies such as CIDOC CRM [10,37] for cultural heritage assets.

In this setting, research efforts concerning the maintenance and diagnostics of CH buildings focus on two themes: the condition assessment and the integration of monitoring data for Structural Health Monitoring. As a heritage-specific process, most of the modeling effort for elaborating Knowledge Graphs revolves around the CIDOC CRM ontology suite whether for describing masonry building decay by integrating spatial data and annotations [38] or restoration reports on a wooden building in a Heritage BIM framework [39]. DTs are used to embrace condition assessment in the scope of risk management and prevention policies design [40,41] and foster decision-making for restoration [42].

Nonetheless, DT applications for CH are still in their early stage for building conservation [43] as the field is in consolidation phase due to the scarcity of validated implementations. Structural Health Monitoring focuses on the integration of the quantitative data output from sensors. CH buildings applications benefit from the modern infrastructure monitoring driven by Internet-of-Things (IoT) sensor management such as for dams [44], bridges and built assets grouped in a DT collection [31]. Hence, comparable monitoring approaches are applied to masonry buildings [45] and on heritage wooden structures with a BIM-based framework [46].

Both BIM and DT modeling paradigms are purpose-driven, prioritizing on building description and model synchronization. They are model-centric approaches, relying on the curation and update of a single representation as a consensus between the experts and stakeholders. Challenges remain in coupling different representations of the built asset, such as different models and multiple surveys, and organizing the eventual concurrencies or interpretation clashes between them.

3. Methods

The development of a Knowledge Graph requires domain-specific knowledge modeling and data enrichment via an information system. As a domain, the structural diagnosis of a cultural heritage building overlaps AEC and CH fields. Although it is positioned at the intersection of these fields, it relies on a union of their requirements and knowledge sets.

In Section 3.1, we introduce the knowledge capture and requirement elicitation activities, forming the foundation for knowledge modeling and system design. We leverage the Semantic Web stack for building the Knowledge Graph as a managed RDF Dataset, using ontology design as the core knowledge modeling approach. Our methodology uses the Xtreme Design methodology [9,47], focusing on the reuse and integration of Content Ontological Design Patterns (ODPs), with Methontology [48], which supports iterative and reusable ontology development. By following a test-driven workflow, we extract and integrate ODPs, primarily from the CIDOC CRM ontology, to accurately represent the knowledge domain. (Section 3.2.). Finally, we follow the design science guidelines [11] to combine the heterogeneous data sources in the Knowledge Graph. To ensure effective data processing, we organize these sources into specific pipelines, each designed for data enrichment and transformation (Section 3.3.).

3.1. Shaping the structural diagnosis of a building as a domain

The structural diagnosis of cultural heritage buildings, situated at confluence between AEC and CH (Section 2), operates in the complex setting of building construction and maintenance [49]. To delineate the relevant knowledge domain and assess the framework's functionality, our methodology follows standard practices in requirements engineering and knowledge capture [50]. On one hand, the requirements are statements describing a necessary function or feature for a system to achieve or possess [51]. On the other hand, a competency question "is a typical query that an expert might want to submit to a knowledge base of its target domain, for a certain task" [52,53]. Both the requirements and competency questions are trustworthy assertions, refined throughout a project lifecycle, organized hierarchically, and inform specifications from design through implementation phases.

The definition of these statements stems from meetings and dialogues with the experts panels, from systematic reading of the civil engineering scientific literature and from the definition of use cases. Participation and attendance of structural diagnosis activities highlight expert-stakeholder interdependencies and the corresponding domain expectations, especially in disaster relief scenarios. A thriving part of the civil engineering scientific literature investigates the structural diagnosis of masonry cultural heritage buildings. Several case-related studies offer in-depth insight in surveying, monitoring or modeling mechanical phenomena, underpinning the sensibility and impact from one task to another: Parent et al. [54] devises a methodology to evaluate the stability of a structural compound by examining the stability regimes of its components, Ferrante et al. [55] examines a Block-Based Model sensitivity to the geometric accuracy of masonry apparel approximated from a point cloud survey. Finally, the use cases provide generalized scenarios that strengthen the connections between domain entities and ensure applicability. Considering these three sources, it is worth noting that not all contained assertions are explicit. With the aim of revealing implicit assertions, we conducted semiotic topical analysis to capture and consolidate analogies, reconciliations, and comparisons in the domain.

In addition, System Engineering [51,56] provides efficient tooling to unambiguously identify and describe the flow of tasks, information and objects between asynchronous activities in a complex setting. A hierarchy of diagrams reveals these flows at different scales and between different layers of information [57], outlining the convergence points and possible feedback loops between the activities, and thus the relevant experts (Fig. 3).

Competency questions and requirements are increasingly connected statements as the knowledge domain and system are refined. They provide a foundation for reusing existing ontological patterns to compose the knowledge graph' supporting ontology, and guide the effective integration of structural diagnosis data.

3.2. Ontology reuse for knowledge graph design

A considerable number of ontologies has been built and made available in open repositories as shared conceptualizations [25]. Ontologies can be categorized by the scope of the objects they describe, which reflects their level of abstraction. Application ontologies directly model specific tasks or objects, representing a single viewpoint from either a user or developer [58]. Domain ontologies "define concepts from a given domain" [48], developed from a consensus among users. Core reference ontologies incorporate multiple viewpoints within a domain, capturing the essential concepts and relationships. Finally, *upper-level* ontologies define "general concepts that are highly reusable across several domains and applications" [48], like primitives from a metamodel to structure new ontologies. Even knowing that an ontology is often more expressive than its initial purpose [53], direct reuse of an ontology is as much the best-case scenario as it is unusual: an existing ontology seldom fits precisely with the requirements of the Knowledge Graph being constructed. Still, ontology reuse is more cost-efficient of an approach than ontology building from scratch, and trusts, on a wider scope, a common conceptualization across datasets.

Ontology reuse relies on methods for relating existing yet distinct ontology components. It encompasses the range of approaches bounded by ontology fusion and ontology integration [48]. On one hand, fusion aims at unifying knowledge from source ontologies in a single one. On the other hand, ontology integration aims at assembling source ontology modules through extension, specialization, and modification operations to achieve consistency across the network of modules. Critical issues arise when reconciling different knowledge models. While the most basic driver for ontology reuse is its content - i.e. the terminology and relations between domain-specific entities -, the major challenges lie in evaluating the compliance between ontological statements and reconciling asymmetric abstraction levels.

According to the intricacy of the domain and the existing ontological material, we rely on the eXtreme Design (XD) methodology for ontology reuse. XD is founded on the application, use, and definition of Content Ontology Design Patterns (ODPs). Content ODPs are small-scale ontologies acting as building blocks, which are to bridge typical problems with specific instantiations [9]. Thus, XD is a method for ontology reuse that falls under the category of the ontology integration approaches. By utilizing Content ODPs drawn from *upper-level* ontologies or extracted from existing *core*, *domain,* or *application* ontologies, the aim is to compose a cohesive network of ODPs that combines the unique

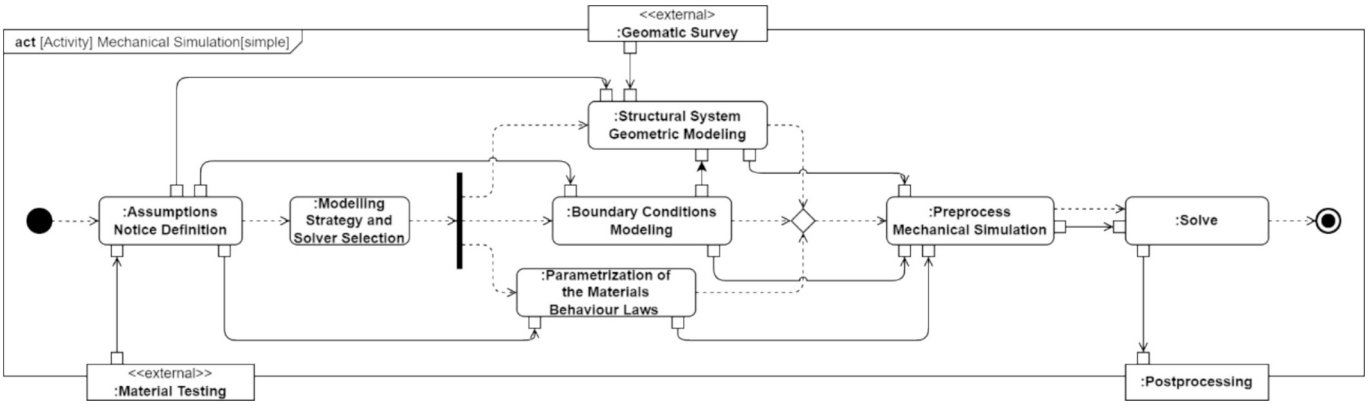

Fig. 3. SysML Activity diagram outlining the tasks and information flows tied to numerical simulation preparation, modeling, and computing.

capabilities of each ODP with those that emerge from their integration. Looking at the XD iterative workflow, each iteration starts with the selection of a User Story and Competency Questions, which are generalized and then matched with Content ODPs. The selected Content ODP is then integrated with the pre-existing ones to form the ontology. Finally, a resource proper to the newly integrated ODP or transversal to the resulting ontology can be documented and exposed in a knowledge system. This process is illustrated with the *Builtwork* resource in Section 4.1.

We characterize the domain's intricacy by a cluster of key themes branching from AEC and CH fields: (i) building features description, (ii) simulation models description, (iii) spatial indexing of information with respect of topology and geometry, (iv) time indexing of information with respect of dates and events, (v) activities and process description, (vi) epistemological stances indexing fact, possibility and interpretation. XD manages the increasing complexity of the corresponding knowledge modeling activities and products due to its modular and iterative nature. In terms of existing ontological material, two standards emerge for delineating AEC and CH domains. IFC is a monolithic domain ontology for construction and facility management industries [59]. CIDOC CRMcore is a formal ontology for the CH field [60] with a family of modules broadening its scope. Both IFC and CIDOC CRM are large, interoperable schemas [37]. As a pattern-based methodology, XD facilitates the selective extraction and reuse of pertinent parts for the target domain.

By separating highly reusable Content ODPs from their domain-specific adaptations, this approach highlights the coexistence of abstract entities crucial for inferring, and attributes essential for recording domain data but with minimal impact on inferences. A key illustration in our domain is the terminological coverage, encompassing domain-specific terms used by experts to denote structural diagnostic activities, techniques, or study objects like materials and alterations, without affecting inference. As a result, we choose to delegate the terminology to external SKOS thesauri, benefiting from existing resources like the BRGM resources for description of stones [61], the Getty' Art and Architecture Thesaurus for categorizing structural elements and

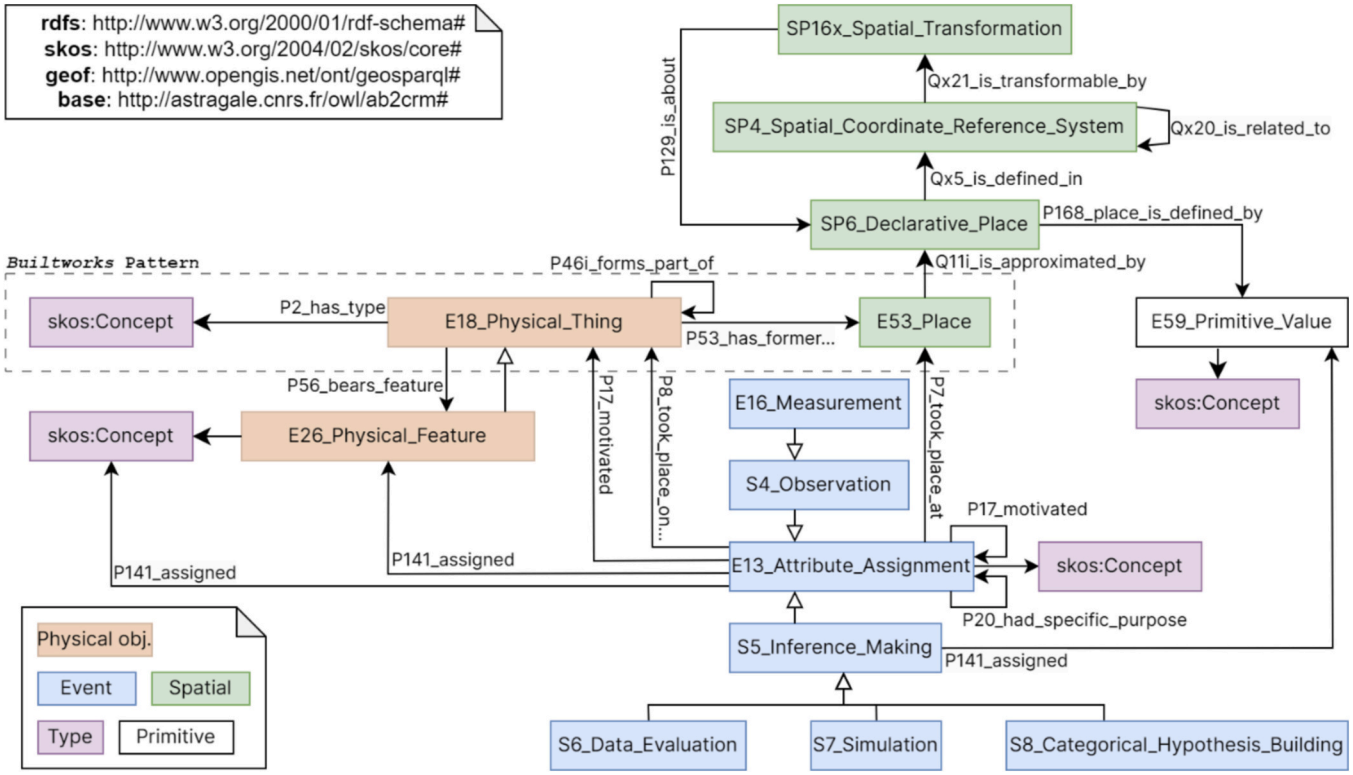

Fig. 4. Resulting ontology schema.

components [62], or ICOMOS multilingual glossary of stone alterations [63].

Successive iterations of this approach yield a compact schema, primarily built from CIDOC CRM extracted Content ODPs for modeling structural diagnosis knowledge (Fig. 4) We combined XD iterations with Methontology to model the most constrained Content ODPs of our domain, such as information spatialization and provenance. Spatial indexing of information relies both on topological relations between abstract places and their diverse geometrical representations. We select modules from CRMgeo and GeoSPARQL [64] to bridge these entities with the RCC8 topology model [65]. The corollaries are: (i) circumvent the systematic 3D geometry querying at the system level; (ii) ability to compute topological relation between places that shall exist but have not undergone geometric survey or modeling activities. The temporal indexing of activities is supported by CIDOC CRM through its management of events. According to this approach, Content ODPs host the consequence of an event that has seen or caused the production of the information. Information production events can be described in greater depth by referencing a type from a SKOS thesauri or with the definition of an epistemological stance via CRMsci and CRMinf entities [66,67]. Each event shall be related to another, thus forming a chain of events mirroring the structural diagnosis process from the information perspective. This enables solid provenance elicitation of information by the reification of the related entities [68].

3.3. Knowledge graph publication

Knowledge Graphs provide a means to structure the meaning of resources and link them. Once embedded in a knowledge system, Knowledge Graphs can be managed, enriched with the integration of verified data from various sources, used as a support for data analysis, and as a support for publishing resources in a human-readable and machine-processable format. Methodologically, we emphasize on designing jointly the knowledge system and the knowledge model (Section 3.2) to avoid over-conceptualization and ensure practical operability. Using the design science framework, we create and validate a knowledge system as a purposeful artifact for a specific domain [11]. We implement the knowledge system as a proof of concept and validate it with real structural diagnosis data (Section 4.). If the context and requirements for the system arise from structural diagnosis as a knowledge domain, the system is further determined by (a) the type of data considered, (b) the type of sources, and (c) the knowledge modeling method.

The diversity of data products stemming from the studies of CH masonry buildings relates to two types of data: operational and scientific data. Operational data management is conditioned by business logic, while research-related data are shaped by epistemic requirements [69]. Both of them benefit from the "Findable, Accessible, Interoperable, and Reusable" (FAIR) guidelines to build an operable and trustworthy knowledge base. These guidelines are widely acknowledged by the scientific community [70], but they need ad hoc adjustments in privacy and access policies to meet business requirements [71]. Nonetheless, these guidelines inform system specifications to ensure machine actionability and human readability of resources. Conversely, heterogeneous data sources come with diverse data products. The data influx is marked by (a) low volume, primarily made from the data relationships and the weight of raw survey and simulations; (b) intermediate velocity, except for SHM, all studies are satisfied with batch or near real time; and (c) high format and meaning variety. This emphasizes the system's need for flexibility and adaptability over scalability in the perspective of volume, velocity, and variety as big data characteristics. Finally, knowledge modeling led us to use eXtreme Design (XD) (Section 3.2.). This method features short iterations, where each cycle's validation conditions the start of the next. As a test-driven approach, it relies on a knowledge system to support procedures and perform validations, adding further system specifications.

Knowledge system design is supported by conceptual and technical references, which require curation or revision for Knowledge Graph implementation. In line with the heterogeneities of data and the complexity of resources prompted by the domain, we consider the use of Semantic Web technologies over property graph solutions for formatting the Knowledge Graph as a RDF Dataset [22]. This design decision defines the knowledge system with an existing technical framework. From a system architecture perspective, the diversity of data sources promotes the design of a distributed and flexible system, where modularity allows for the gradual addition of services as new sources and functionalities are introduced. We therefore envision the system architecture as event-driven, with interactions between microservices choreographed through event flows. By microservices, we refer to deployable, independent services that isolate specific tasks and are bound to collaborate to address elaborate functionalities [72]. In this context, choreography is a service coordination method where each microservice operates autonomously but produces or reacts to events by exchanging messages via a central broker. This approach results in a loosely coupled system (Fig. 5) that can evolve to handle both basic and sophisticated functionalities, seamlessly integrating various data flows and computational processes into coherent data pipelines [73]. The modular, event-driven nature of the system ensures adaptability as demands grow in complexity. A meaningful example concerns the Extract-Transform-Load (ETL) tasks. A simple data pipeline for an ETL task triggers only the API gateway and RDF Integration Service. As data requirements grow more complex, such as adapting existing semi-structured data or extracting unstructured data, the data pipeline is extended by adding ad-hoc mediation services [74].

We outline the system architecture by following the data flow from data collection to data publication through the stages of collection, ingestion and enrichment, storage, analysis and processing, and publication.

During data acquisition, an API gateway centralizes the data flows coming from user interfaces or services within existing CH ecosystems [77]. Each route within the API is mapped to a dedicated pipeline for processing resources.

During data ingestion, if the incoming textual data complies with the pipeline specification, it is serialized and stored in JSON format within the body of a message, which is published to a topic within the message broker. If the input data includes a binary file, the file is first uploaded to the Data Lake, with its location reference included in the message. Each message features a unique key generated by combining the data pipeline identifier and a UUID, while their body holds the data to be cast as RDF Data in the Knowledge Graph. The message broker employs a publish/subscribe mechanism, where services – such as the API Gateway - publish messages to topics and others consume them. As a consumer service, the RDF Data Integration Service acts as a stream processor, updating the Knowledge Graph using templated SPARQL Update queries. The template corresponds to the data pipeline specified in the message key, with its fields populated by the message body data. The outcome of each update operation is logged into a dedicated topic of the message broker, facilitating the monitoring of the microservice's instances.

Two databases provide the data storage solution: *GraphDB* as an RDF Triplestore, a structured graph database designed for the storage and retrieval of an RDF Dataset, and *Minio* as a Data Lake, an unstructured database solution to store raw or binary data. The knowledge graph, residing in the RDF Triplestore, captures resource relationships and links to binaries in the Data Lake, adding a semantic layer with metadata and provenance information.

Additional data analysis and processing are necessary for certain ETL or processing pipelines. For example, ingesting semi-structured data from the Aioli platform's external document store requires preprocessing before updating the Knowledge Graph (Fig. 5). Regarding the data publication side, enhancing information retrieval or deriving additional knowledge from the graph may also necessitate further processing.

Finally, the data is published via an API and SPARQL endpoint, with

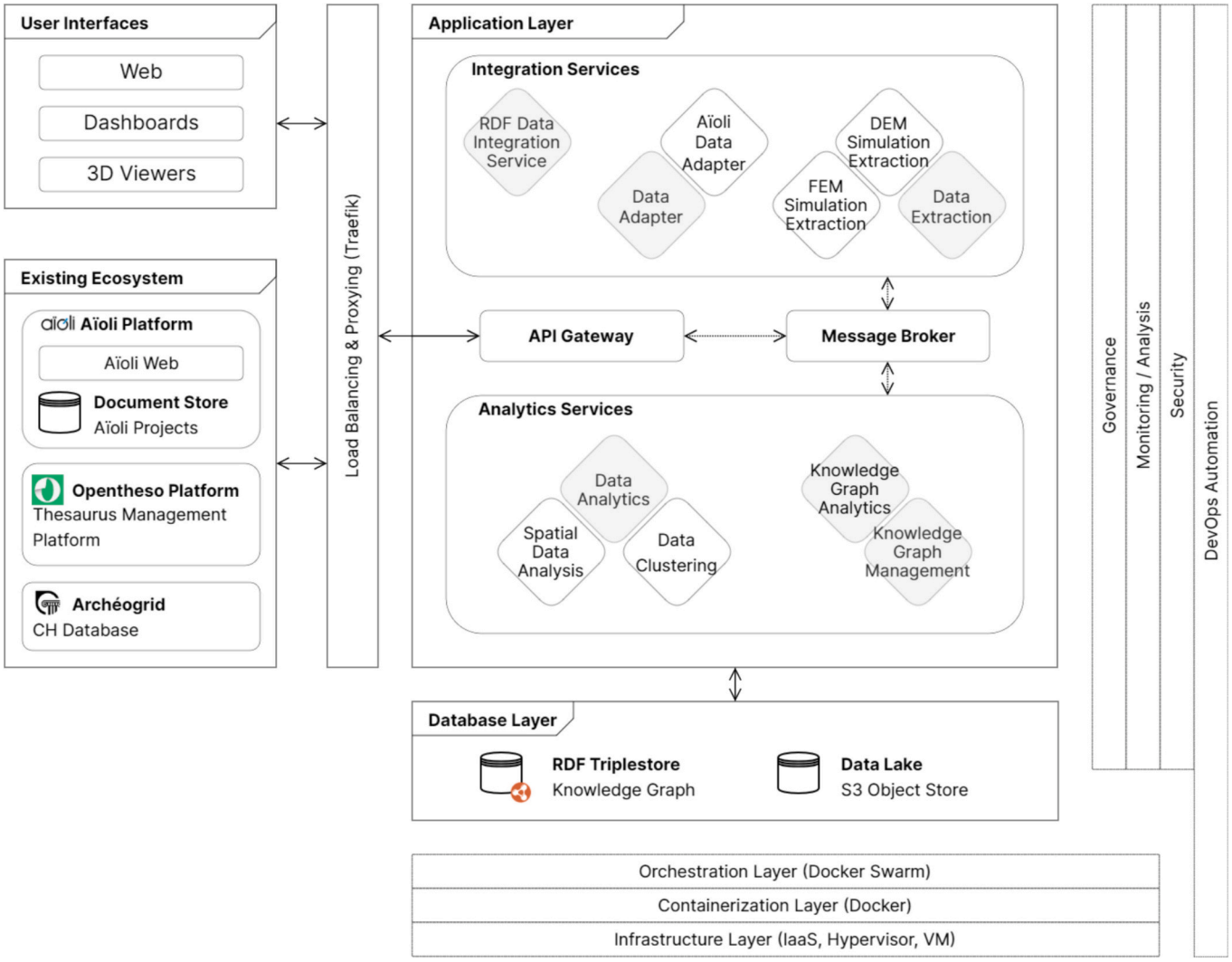

Fig. 5. High-level overview of the knowledge system architecture, based on modern service-layering [75,76].

the API mediating data for easier management and ergonomics, shielding users from RDF complexities. A web service interfaces with the API to facilitate resource interaction and visualization.

4. Results

In this section, we integrate structural diagnosis data as meaningful resources for effective storage, processing, and visualization. Using the Notre-Dame de Paris flying buttress diagnosis use case, we demonstrate knowledge modeling of the *Builtworks* resource, describing buildings and structural components (Section 4.1). We then focus on the *Builtworks Feature* resource, aligning the degradation phenomena data documented through visual inspection and simulation models. Instances of this resource are linked by type, spatialization within the built asset, and provenance. We curate these instances by modifying visual inspection data from third-party services and extracting simulation predictions from their time series results (Section 4.2). Finally, we demonstrate information retrieval and processing to publish the resource and provide scenario insights (Section 4.3).

We support these operations by a Proof-of-Concept (PoC) implementation of the knowledge system (Section 3.3). It features all the services for Data Collection, Ingestion, Processing and Publication (Fig. 5), with the sole difference that the processing services are delivered by a single API, and the Web Dashboard is planned for the prototype version as it is not a core service. The deployment scripts, services codebase, and supporting ab2crm ontology are available in the GitHub repository (https://github.com/prj-astragale/). We tested the services individually and performed an integration test with the Notre-Dame flying buttress diagnosis.

In the aftermath of the April 15th 2019 fire, a comprehensive diagnosis supported Notre Dame de Paris Cathedral's recovery [5,78]. Significant structural damage resulted in the destruction of the carpentry and impairments of the vaulted stonework, such as a breach in the northern transept voussoir paneling (12th), the collapse of a nave arch (12th) and of the transept crossing vault (19th) (Fig. 6).

The vault's stability relies on the careful proportioning of their buttressing system to efficiently route the thrusts caused by the weight of the vaults, the covering carpentry work and the wind loads. The design solution brought by the Gothic style is the flying buttress. An arched structural device, set into the load-bearing wall at the level of the vault haunch that shifts the thrusts onto an offsetted abutment (Fig. 7). The principal collapse mechanisms originate from the rupture of equilibrium between the thrusts of the vault and the buttressing system. The vault thrust exceeding the buttressing's is referred to as *passive thrust mechanism*, and the opposite case as *active thrust mechanism*. Both scenarios are outlined by the apparition of hinges in the buttressing system corresponding to the rotation of stone blocks. They are evidenced by crack patterns in the masonry [78,79].

Scaffolding facilitated visual inspections and sound velocity measurements, revealing cracks in two choir flying buttresses (Fig. 6).

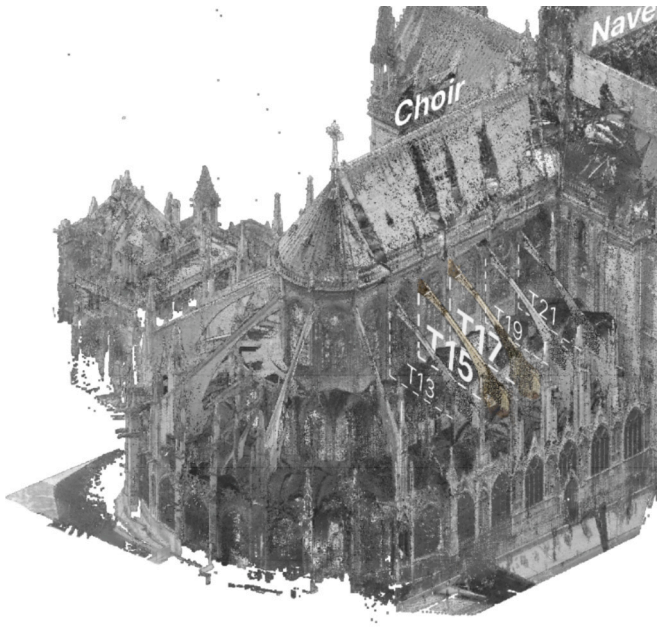

Fig. 6. Location of choir flying buttresses with a crack observed at the head.

Mechanical simulations can help to determine if the cracks occurred before or after the partial collapse of the vaults and the carpentry loss. The aim is to correlate observed cracks with predicted crack patterns from *active* or *passive thrust mechanisms*.

4.1. Baseline: the craft of the Builtwork resource

An iteration of XD results in the development of a new resource type for the Knowledge Graph (Section 3.2). The outputs of this process include the curation of a Content ODP with the appropriate classes and relations (TBox), the selection of metadata vocabularies and thesauri for recording the resource's instances attributes (ABox), and the design of SPARQL query templates and validation schemas necessary for configuring the resource's ETL pipeline. These components are documented and work together to ensure seamless integration of new instances into the knowledge graph.

As a baseline for demonstrating the methodological steps, we curate the *Builtwork* resource in charge of describing the buildings and its structural components. An iteration starts by selecting the corresponding User Story and Competency Questions (CQ) (Table 1). Issued from knowledge capture, they frame the resource in the domain: the CQs establish the foundation for the user queries while the user story relates them to the context. This is followed by the Generalization Tasks, which aim to translate these assertions from natural language to more formal statements that "express possible inferences or other rules that apply to the concept" [52]. Conversely, the Generalized CQs are as straightforward as the Generalized User Story: "Different built structures form another structure, with various types".

The next step consists in curating the Content ODP that accurately carries the resource meaning according to the generalized assertions. Given that our domain is at the intersection of the AEC and CH fields, we identified IFC and CIDOC CRM as candidate ontologies for curating the *Builtwork* ODP. Several classes and properties from CIDOC CRM exactly match the generalized statements: the self-referenced property *crm:P46i_forms_part_of* allows to replicate the hierarchical composition of structural components, the class *crm:E22 Human Made Object* describes a persistent physical object of which the spatial extents are defined by *crm:E53_Place*. We extract these CIDOC CRM classes and properties (TBox), compose them with *skos:Concept* from the SKOS ontology to manage entity typing, and then document the resulting Content ODP (Fig. 4).

The Content ODP Integration and Pipeline Design phase bridges knowledge modeling with the technical aspects of data integration. First, the Content ODP is integrated into the actual ontology that has been built from the previous methodology iterations. In order to derive the *Builtwork* resource from the *Builtwork* ODP, we then select the domain-specfic metadata vocabularies and thesauri to describe the attributes of a resource instance. Given the lack of domain-specific metadata vocabulary for the target, we opt for the Dublin Core [80] and schema.org [81] vocabularies. For categorizing the different types of buildings and structural components, we use the Getty' Art and Architecture Thesaurus [62]. The products of this phase are: the JSON Schema for data validation, the templates of the SPARQL queries for "Create,

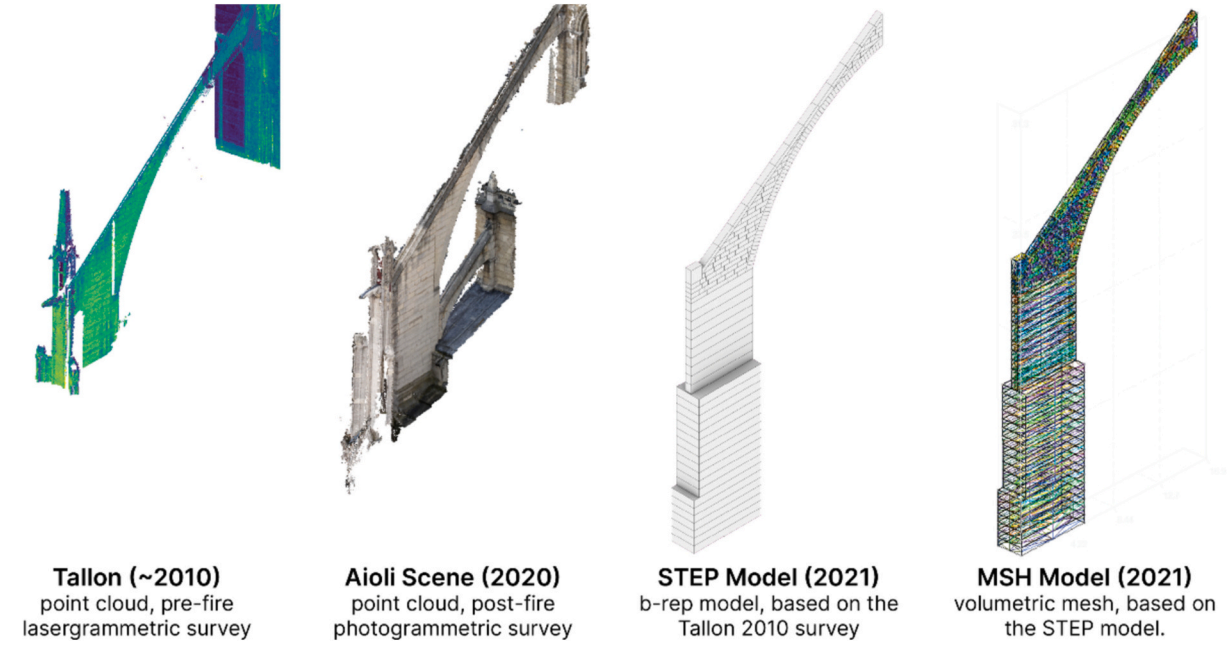

Fig. 7. Four geometric representations of the T17 flying buttress: pre-fire lidar and post-fire photogrammetry surveys, STEP and MSH models for supporting mechanical simulation. Each geometry is stored in the Data Lake and linked in the Knowledge Graph.

Table 1
Seven steps of the methodological continuum, from the use case narrative to the publication of routes for interacting with *Builtwork* resource.

Use Case Narrative and User Story	The T17 flying buttress, the T19 flying buttress and the CH1518 vault are structural components of the cathedral Notre-Dame de Paris. While the arches are more recent (19th century), the vault dates back to medieval times, between 1163 and 1200.
Competency Questions	What is the name of the built asset? What is the construction date of the built asset? Give a summarized description of the built asset? Which are the *components* of a *building*? What is the *type* of a *building*?
Generalized Constraints	A *building* and its *components* are *Builtworks*. *Builtworks* have none to many *types of Builtworks*. *Builtworks* have one *identifier*. *Builtworks* can be hierarchically related. A *Builtwork* shall not be part of itself. A *Builtwork* designates an immovable object, at a specific *location*.
Generalized Competency Questions	What is the type of a *Builtwork*? Which *Builtworks* are part of a *Builtwork*?
Content ODP	(Fig. 4)
Content ODP Integration and Pipeline Design	(JSON Schema) Builtworks (SPARQL) Create, Update and Delete SPARQL templates (SPARQL) Select and Construct SPARQL templates
Implementation and Publication	(POST) https://{INLAKE_HOST}/builtworks (GET) https://{INLAKE_HOST}/builtworks?recursive = {bool}?graph = {bool} (GET) https://{INLAKE_HOST}/builtworks/{builtwork_id}

Read, Update, Delete" (CRUD) operations, and the processing methods for complex data integration cases (Table 1.).

Finally, the resource-specific pipeline implementation within the knowledge system ensures dynamic knowledge graph updates and resource publication. It enables the development of data-driven analytics and ad-hoc visualization. Testing forms the backbone of a successful iteration. We facilitate the design and implementation of a resource' related unit tests, which can be triggered at any step at the Knowledge Graph management service (Fig. 5).

The succession of XD iterations results in the addition of ressources types manageable through the Knowledge Graph. Accordingly, the ontology (TBox) is expanded with the integration of the corresponding ODPs. Therefore, the *Builtwork* ODP serves as a dependency for ODPs such as the *Geometry* ODP, aimed at managing the typology and geometry of a place within the building, or the *Builtwork Feature* ODP, aimed at describing characteristics or phenomenon pertaining to the structural components.

4.2. Recording the surveys information and the simulation results

The visual inspection of the Notre-Dame de Paris buttressing system has been transcribed as annotated point clouds using the photogrammetric annotation platform Aïoli [13]. These point clouds are produced using photogrammetry techniques from a sequence of photos of the building after the fire to serve as a basis for an Aïoli scene (Fig. 8). Each scene contains the 3D point cloud (Fig. 7.b), the spatialized photograph, and different annotation layers. Each annotation associates a subset of the point cloud to user-defined labels, which structure varies depending on the kind of diagnosis the layer is referring to. The conservation-restoration layer indifferently holds information about observed alteration on the masonrywork – such as cracks, displacements of masonry panels, stone weathering – and forecasts of conservation-restoration activities to be delivered. This information is formatted as a list of informal statements: descriptions such as "Altered stone, to be replaced" or "Crack in the mortar". Other information complement this layer, like sound velocity measurements [6] for the mechanical characterization of stones and identification of cracks in the mortar indiscernible to the naked eye.

From a technical standpoint, the Aïoli scenes are stored in a document-oriented database specific to the platform. We retrieve the semi-structured information held in the database to the Knowledge Graph with an Extract-Transform-Load (ETL) process. A first Transform process occurs in the Data Adapter service (Fig. 5), with the aim of formatting incoming data to fit an existing resource, then we reuse the resource pipeline to update the Knowledge Graph. Considering the conservation-restoration layer, we target the *Builtwork Feature* resource for loading information about an observed alteration on the masonry. For each annotation, the point cloud subset can either be embedded in the Data Lake, internal to the system, or linked via a reference to its

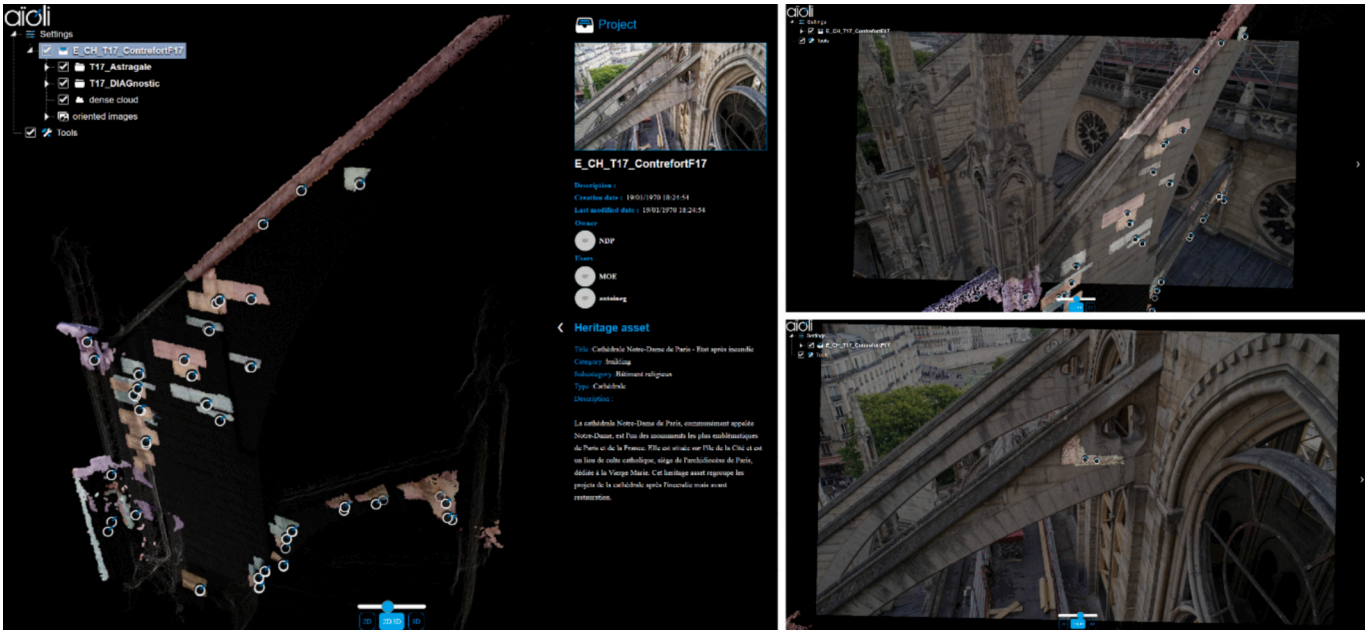

Fig. 8. Visual survey masonry information recorded on the Aioli platform, with annotations applied to both the photogrammetric point cloud (left) and corresponding photos (right).

location in the external Document Store of the Aïoli platform (Fig. 5). The information associated with this geometry consists in an informal description, metadata, and thus lacks a consistent way to describe what feature has been observed. In addition to the formatting of the data in the Data Adapter service, we derive a reference to a controlled vocabulary from the informal description. We perform fuzzy string matching with the comparison of the Levenstein distance (reference) to align the description with one of the entries ICOMOS glossary for stone alteration [63] formatted as a SKOS thesaurus. For instance, the annotations featuring a "Crack in the mortar" are labelled with the *icomos-stone:Crack* reference. Finally, the formatted data is sent down to the *Builtwork Feature* pipeline to update the Knowledge Graph accordingly. In compliance with the *Builtwork Feature* ODP, the annotations generated in the Aïoli platform (*crm:E13_Attribute Assignment*) denote on-site features (*crm:E26_Physical_Feature*) observed (*crmsci:S4_Observation*) on structural components (*crm:E22_HumanMade_Object*). They are spatially indexed within photogrammetric point clouds (*crmgeo:SP4_Declarative_Place*), depicting the geometric extents (*crm:E53_Place*) of components in a specific spatial basis (*crmgeo:SP4_Spatial_Coordinate_Reference_System*).

The simulation results are recorded by the simulation solver as time series recording the evolution of the physical properties of mechanical variables. We use LMGC90 multiphysics solver [19] to perform two simulations of the Notre-Dame de Paris buttressing system evaluating the principal collapse mechanisms known for Gothic flying buttresses: *active thrust* and *passive thrust mechanisms*. Despite following different scenarios, these simulation models share the same initial state, material model and geometric model. The latter is a volumetric mesh (Fig. 7.d), computed from the STEP model (Fig. 7.c), designed from both the Tallon laser survey (Fig. 7.a) and the specifications of the targeted simulation modeling strategy. LMGC90 is based upon the Discrete Element Method (DEM), one of the Block-Based Modeling (BBM) strategies to solve the interactions between entities (Section 2.1) (Fig. 9). Masonry apparel is represented as discrete blocks interconnected by cohesive interfaces reflecting mortar behavior, with their physical properties recorded in the time-indexed tables of a HDF5 file. The condition of the mortar is represented by the gap between two blocks and a damaging variable.

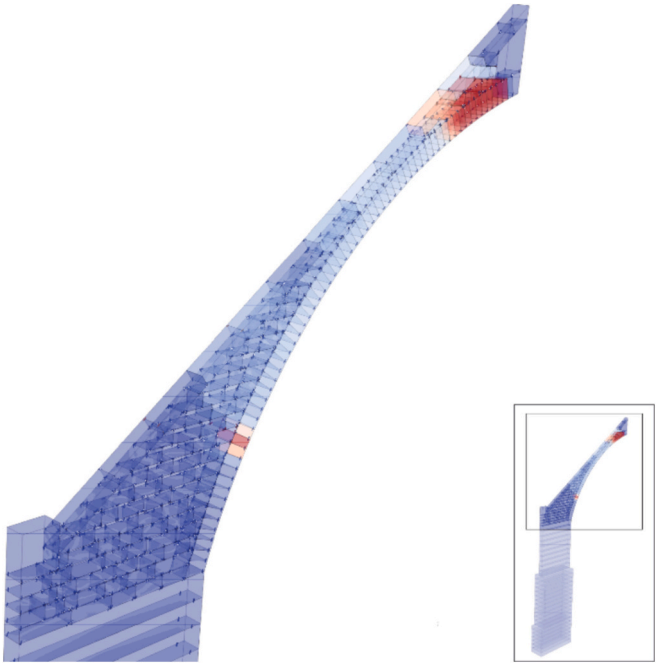

Fig. 9. Mechanical simulation prediction for a choir flying buttress under active thrust load. The DEM-based LMGC90 solver outlines block panel rotation and the apparition of a crack at the head of the flying buttress.

Hence, data that evidence a predicted crack is discrete to the time and the entities. Provided with connected components algorithm and graph operations, we retrieve chains of damaged interfaces along simulation steps and geometry topology, and represent them as a disjoint set of graphs. In other words, we retrieve the predicted evolution of cracks within the mortar.

Consequently, we craft a *Builtwork Feature* resource similar to the surveyed one. We annotate the geometric model supplied for the simulation with the prediction of a crack and update the Knowledge Graph accordingly. These annotations are derived from (*crmsci:S6_Data_Evaluation*) LMGC90 simulation (*crmsci:S9_Simulation*) denote on-site features (*crm:E26_Physical_Feature*) predicted (*crmsci:S4_Observation*) on structural components (*crm: E22_ HumanMade_Object*). They are spatially indexed within the geometric model (*crmgeo:SP4_Declarative_Place*), depicting the geometric extents (*crm:E53_Place*) of components in a specific spatial basis (*crmgeo:SP4_Spatial_Coordinate_Reference_System*). Fortunately, the information conveyed by these annotations is structured and univocal as they refer to the *icomos-stone:Crack* concept in the SKOS version of the ICOMOS glossary for stone alteration [63].

The interrelations between visual inspection, on-site measurements, and simulations are established at the knowledge model level. By elicitating the meaning of these complex data products, instances (TBox) are accurately aligned and published as *Builtwork Features* resources. These resources are typed using SKOS Concepts, expose metadata structured with existing metadata vocabularies, are linked to the *Geometry* resource they are derived from, have their production event identified with SKOS Concepts (Fig. 11) and linked with the resource dependencies as a provenance chain.

4.3. Provenance-based and spatial insights for the diagnosis

As the diagnosis question concerns the existence of cracks in the mortar whether pre- or post-fire, the *Builtwork Feature* is a central resource for supporting analysis and interpretation. Querying the *Builtwork Features* attached to the studied T17 flying buttress retrieves all of them, independently from their meaning or origin. They can be filtered to isolate only the crakcs, identified as *icomos-stone:Crack*.

Event-based knowledge modeling roots on the production events relative to the documents and resources, thus forming an efficient basis for provenance retrieval as it lowers the cost of storing the dependencies of a resource' production. A *Builtwork Feature* documenting an *icomos-stone:Crack* issued from simulation post-processing unveil a deeply layered provenance (Fig. 10.a), while the one from the alteration survey displays a shallow one (Fig. 10.b). Epistemological stance is registered at the ontology level (TBox) and linked to the production of a resource and its dependencies using CRMsci classes *crmsci:S4_Observation* for measurement and surveying, and *crmsci:S8_Categorical_Hypothesis_Building* or *crmsci:S9_Simulation*. Therefore, the layered provenance accounts for the stack of surveys, hypothesis and models contributing to the creation of a *Builtwork Feature* instance (ABox). Multiple *Builtwork Features* can be examined and linked regarding the shared dependencies. For instance, both the *Builtwork Features* in (Fig. 10) are related to the post-fire geomatic survey. The provenance tree can be expanded in an iterative fashion as new information becomes available, for instance adding material model parametrization "Material Rigids CZM" can be deferred with respect to adding geometric modeling of the structural component (Fig. 10).

To conclude on the technical side, the provenance diagram provides a visualization of the recursive SPARQL Construct query addressed to the Knowledge Graph for a resource at the route */process/{resource_id}/event_chain*. Hence, this eases the verification process and responsibility elicitation in the information production chain.

From the perspective of spatialized data, the information held by the *Builtwork Features* is native spatial data. Their simultaneous visualization and their clustering provide a baseline for the interpretation of the

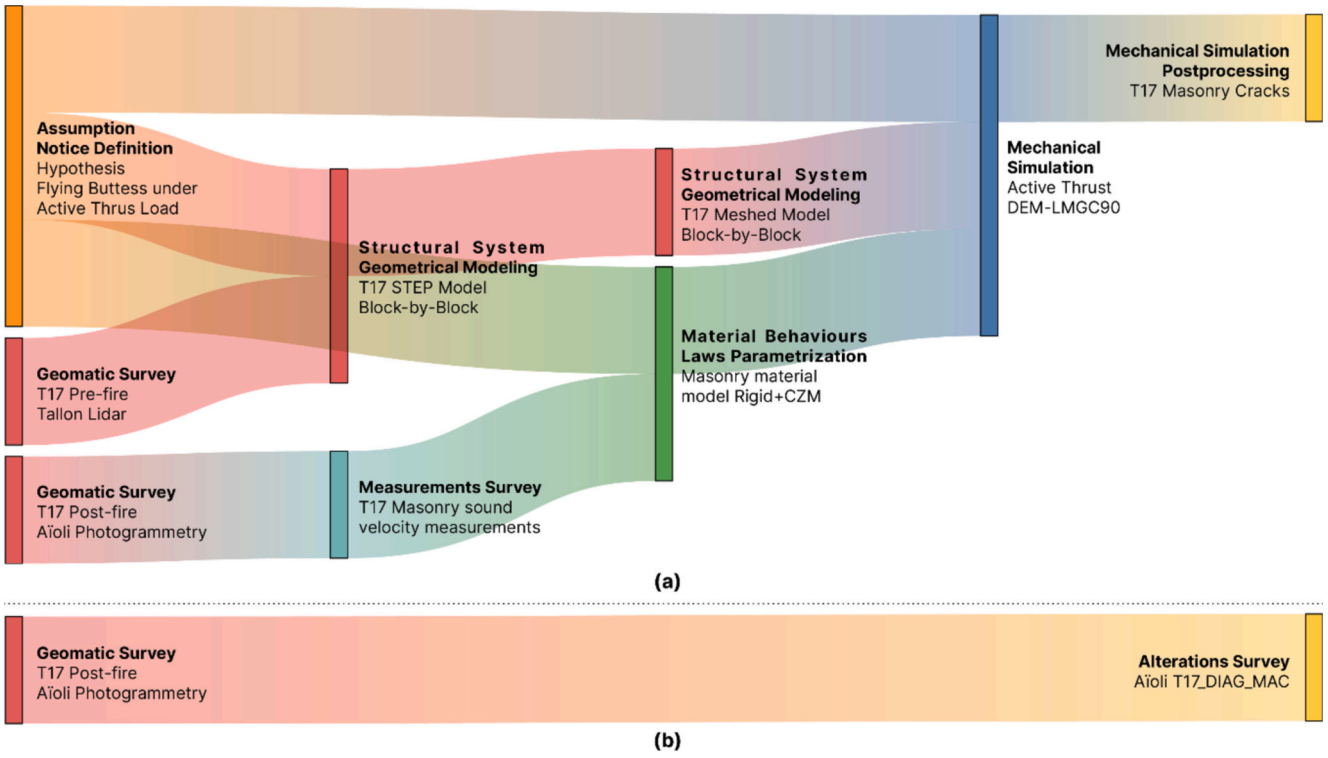

Fig. 10. Provenance visualization for two *Builtwork Feature* instances related to the T17 Flying Buttress: (a) a crack predicted by the *Active Thrust* simulation scenario and (b) a crack observed during the visual inspection of alterations.

phenomena they describe. Each *Builtwork Feature* corresponds to one of the many geometric representations of the structural component - whether measuring or modeling it as a *Geometry* resource - and condition its recording. The instances (ABox) of *Builtwork Features* extracted from the post-processing of DEM simulations are mapped to the STEP model of the structural component, while those issued from the visual inspection are mapped to the photogrammetric point cloud (Fig. 11). The location of each *Builtwork Feature* is documented in the Knowledge Graph by referencing a specific subset of its corresponding *Geometry* resource instance (ABox). Dependencies between the *Geometry* resources are described in the Knowledge Graph - later visualized in the provenance trees (Fig. 10.a) – and their binaries are stored in the Data Lake after having previously been processed through the ETL pipeline.

In an operational setting, the succession of measures and studies with

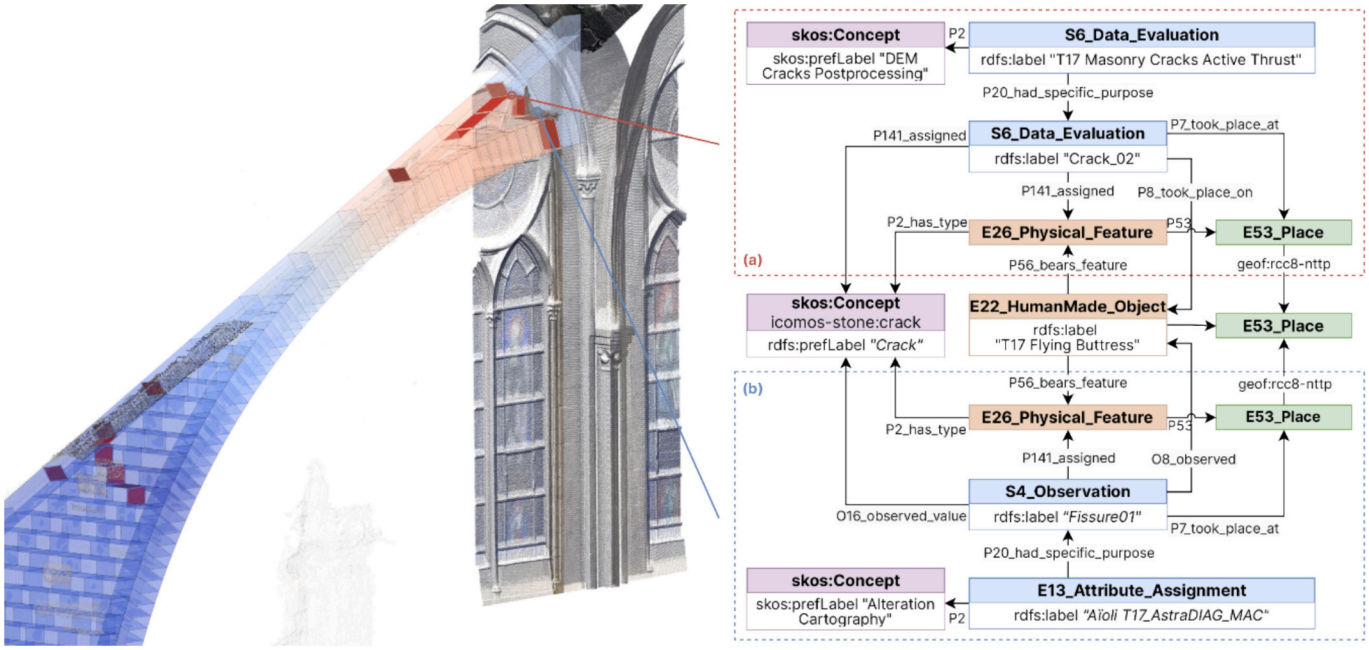

Fig. 11. Joint visualization of two *Builtwork Feature* instances related to the T17 Flying Buttress: (a) a crack predicted by the *Active Thrust* simulation scenario, located on the structural component STEP model; (b) a crack observed during the visual inspection of alterations, located on the post-fire Aïoli photogrammetry point cloud.

varying technologies inevitably leads to a breadth of geometries instantiated without fixed reference in 3D space. The dataset from Notre Dame de Paris buttressing system makes no exception to this common operational setting. The different surveys and models had to be aligned in the same space regardless of whether they come from before or after the disaster [82] (Fig. 7). To leverage the reconciliation of geometries in the same space, we use the classes *crmgeo:SP4 Spatial Coordinate Reference System* and *ab2crm:SP16x Spatial Transformation* in the *Geometry* ODP (TBox) to capture the relations between Spatial Coordinate Reference System (SCRS). This enables the declaration of the 4 × 4 affine transformation matrices to move from a datum to another (Fig. 4.a). At query time, when requesting multiple *Builtwork Features* recorded on different *Geometries* of a *Builtwork*, a common SCRS to the *Geometries* is defined and the related 4 × 4 transformation matrices are computed and retrieven in table to the user. On the technical side, a challenge arises to visualize such a breadth of geometry types: unstructured point clouds with scalars for laser intensity or RGB colors, structured CAD files with volumes registered in boundary representation (b-rep) and structured volumetric meshes (Fig. 7). The *Paraview* suite for scientific data visualization is used for desktop display and interaction with these geometries, further preprocessing is required for online previewing with the *threejs* Javascript graphical library.

Finally, we delineate the clashes, concurrency and complementarity among the *Builtwork Features*, seen as native spatial data via their spatial clustering. Different criteria are available: topological information between *Builtworks* with RCC8 model [65], proximity and topological between the related *Geometries*. In this study, the structural diagnosis of flying buttresses showcases the use of the proximity and intersection criterion. We first reconcile *Geometries* and *Builtworks Features* in the same SCRS, then we compute the Euclidean distance between two geometries' nearest points for the proximity criterion or the convex hull overlaps and containment for the topological criterion. Lastly, we resolve clusters with Ward's method for hierarchical clustering analysis [83]. The clustering results provide two kinds of insights. First, they reveal the correspondences between similar phenomena observed in different studies, enabling the tracking of changes over time through successive visual surveys and facilitating the comparison of model predictions with real-world observations. Second, they help identify hazardous zones, characterized by the concentration of features detected through multiple expert studies. The clustering of the *Builtwork Features* instances (ABox) from the structural diagnosis of the flying buttress outputs six clusters (Fig. 12). In addition to the concentrations of weathering in different parts of this structural component, we observe that the sixth cluster is the only one where a surveyed crack is predicted by a simulation. The corresponding simulation scenario is the *active thrust mechanism*, prompting further exploration and evaluation of this scenario.

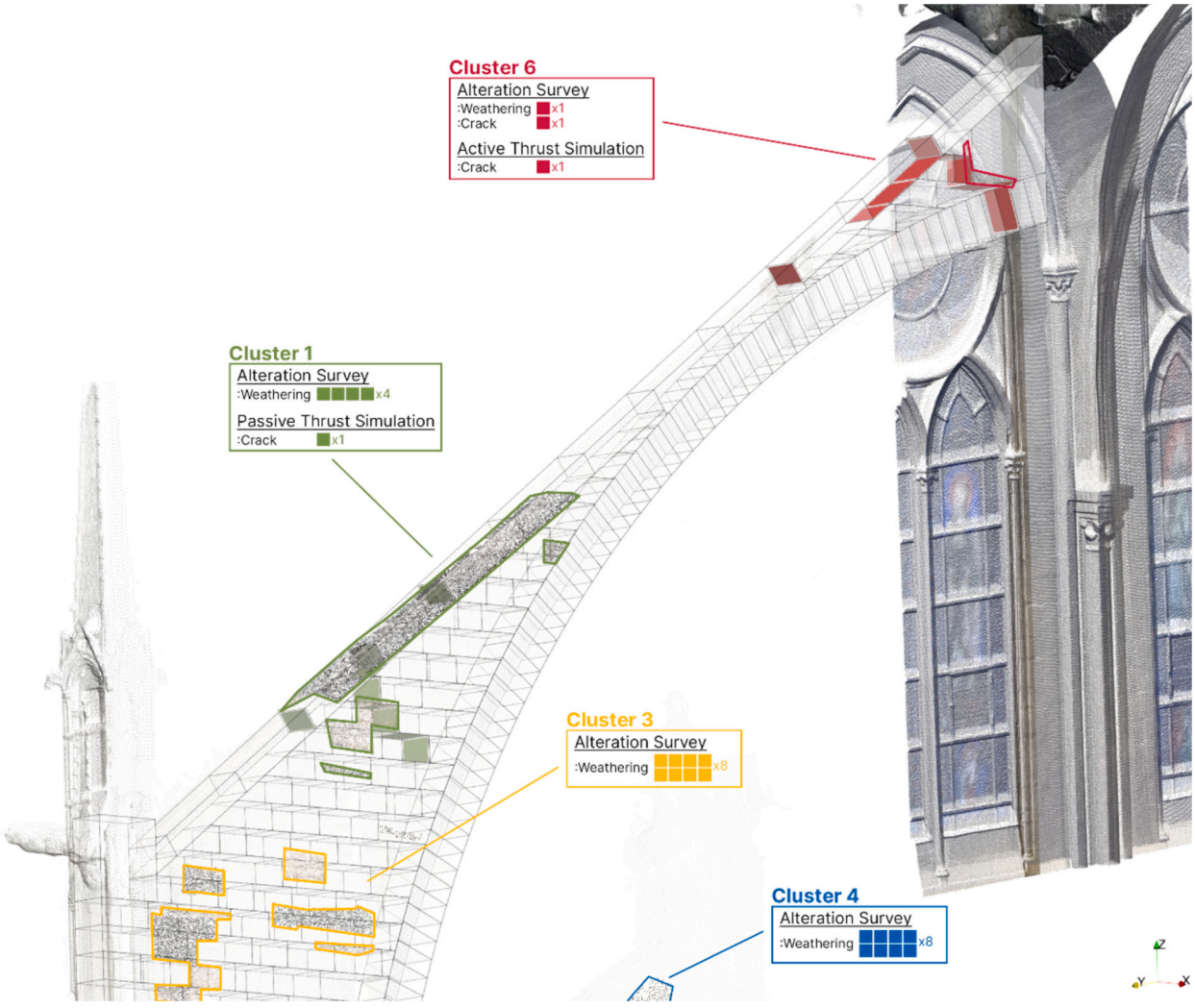

Fig. 12. Spatial clustering results of *Builtwork Features* instances, corresponding to observed or predicted alteration during the structural diagnosis of the T17 flying buttress. Each instance is represented as a square and classified according to its type from the ICOMOS glossary for stone alteration [63].

5. Conclusions

5.1. Knowledge graph for integrating cultural heritage buildings structural diagnosis

A detailed framework for enriching structural diagnosis data up to a Knowledge Graph, an ontology, processing services has been developed with the use of Semantic Web technologies, big data principles and microservices guidelines. Toward knowledge capitalization, the significance of the established Knowledge Graph lies in enabling data sharing between operational and scientific communities, facilitating the evaluation of models against surveyed reality, and supporting knowledge-driven processes alongside with archiving diagnosis studies. More specifically, the degradation phenomena are syntactically and semantically aligned with the description of their provenance and matched with controlled SKOS vocabularies. As natively spatial data, this information is mapped by its position on the structure, its topological relationships and the alignment of its geometries. The contribution of this paper can be outlined as: (a) interoperability between the data products of cultural heritage building diagnosis studies; (b) robust building information spatialization across different modalities; (c) concurrency and lineage of the degradation phenomena competing studies. A main challenge has been the mitigation of the complexity emerging from the combination of those items. Although it responds to the demand of multimodality in the study of a heritage asset, this contribution complements the actual efforts to bridge quantitative SHM data to a simulation model under the DT paradigm, or to structure surveying data in a building digital model. Knowing the scarcity of knowledge system implementations in the CH field, we made a point to support this contribution with the deployment of a proof-of-concept.

A case study based on real structural diagnosis activities is implemented as an integration test for our knowledge system. It was endeavored to evaluate and compare the presence of cracks on Notre Dame de Paris choir flying buttresses. The heterogeneous data influx has been structured as data pipelines, contributing to the information system through an API, data adaptation from third-party services such as Aioli photogrammetric annotation platform for visual inspection, and data extraction from stored raw data such as LMGC90 mechanical simulation results. A Knowledge Graph and a Data Lake are used to store diagnosis data in a structured way. The relationship between the data is sustained in the Knowledge Graph as the diagnosis progresses and the different alternatives of the condition state can be considered. Furthermore, the reuse and ability to link this Knowledge Graph is fostered by the designed ontology based on the standard CIDOC CRM ontology, using the widely adopted metadata vocabularies from Dublin Core [80] and schema.org [81] for the description of the resources, as and relating to domain-specific thesaurus such as the ICOMOS glossary of stone alterations [63] or the Getty's Art and Architecture Thesaurus. Concerning the practical utilization of this data, the queries and inferences are enabled by OWL reasoning, then performed by an API exposing the data as manageable resources. Further processing and analytics are provided by the API to retrieve the provenance of a resource, its spatialization on aligned geometries, and clustering in the case of resources that depicts a degradation phenomenon. They can be consumed by visualization services to facilitate the reading of this processed information. At query time, the user can retrieve a proposition of a condition state from a curated set of degradation phenomena, mixing surveyed reality to predicted scenarios. Therefore, this eases the evaluation by stakeholders and experts of alternative scenarios, supporting decision making for the design of conservation-restoration activities.

5.2. Limitations and critical review

Using Semantic Web technologies to build inteconnected data and knowledge through a Knowledge Graph comes with an invaluable range of advantages, especially in terms of expressiveness, reasoning, knowledge reuse and sharing. However, several limitations tied to its application in this work's framework impact its efficiency in practical operations, and reflect the broader challenges of using linked data as a foundation for associating information across domains.

In this paper, several limitations stem from ontology modeling choices for structural diagnosis as an operational process. First, the condition state of a built asset remains unmodeled, as we opted for a CIDOC CRM event-based framework over a state-based model. The current or projected state of an asset is constructed at query time by selecting features unveiled during diagnostic activities. While this approach enables discussion across several studies, it lacks a formal means to validate or standardize the proposed state. Second, the model does not capture causality analysis, an area where expert knowledge, such as the signification of degradation patterns, is essential. While the proposed framework enables the clustering of similar features affecting the building, the model does not embed the description nor interpretation of degradation patterns. Despite these limitations, the methodology allows for stepwise completion of the ontology with the integration of new Ontological Design Patterns (ODPs).

Expanding the model to convey more comprehensively the structural diagnostic approach - incorporating risk, restoration, and building lifecycle perspectives - highlights the broader challenges associated with linked data. Similar to the work presented, which models a facet of structural diagnosis, other models exist in the literature that depict related concepts. Staying faithful to the original endeavor of reusing existing ontological material via ODPs, open questions remain around creating links between distinct models and their classes (TBox) to achieve ontology alignment and integration. The pitfall being the clashes between the ontologies, resulting in data inconsistency or redundancy. Manual validation and operation are still paramount despite the enhancement of automation support [22]. This question also extends to the maintenance of existing Knowledge Graph Data (ABox) regarding the evolution of a knowledge domain, modeled by ontologies (TBox).

Another limitation stems from the research design, scoped down to conceptual modeling and integration framework design. While CH data is a document-centered practice, often restricted to describing individual buildings. Although the framework provides pathways to integrate and describe CH data, further challenges lie in fostering user engagement and promoting rigorous data management practices. Solving these challenges requires establishing a solid data governance coupled with adapted UI/UX design for efficiently connecting the model to user expertise in CH fields. These elements, essential for reliable input management and effective data usage, remain outside the scope of this study.

5.3. Future outlook

Recording and capitalizing on the structural diagnosis data of cultural heritage (CH) buildings aligns with broader maintenance practices within the Architecture, Engineering, and Construction (AEC) industry, although specific requirements arise due to heritage considerations.

Considering first the structural diagnostis and putting aside the CH diagnostics accountments for unique material, original construction techniques, variance of procedures, impact of the heritage value preservation, both CH and AEC benefit from consolidating various damage representations. This work focuses on reconciling qualitative in situ observations with simulation results, laying the groundwork for future research to bind sensor-based measurements from Structural Health Monitoring (SHM), material sampling and mechanical testing. Building on the ongoing developments in Digital Twins for construction, a central direction for this work is to utilize Knowledge Graph as a backend to consolidate information from corresponding models and enhance insights into structural damage. By connecting multiple damage representations, this approach enables the referencing of a building's current or projected state, related to operational aspects such as risk assessment and the causality between various types of damage. To generate

operational insights, Knowledge Graphs enable two distinct reasoning approaches. One focused on deductive knowledge, leveraging formalized expert knowledge and rulesets tied to common pathological signatures found in well-known AEC structures, like masonry bridges or retaining walls. An open question remains regarding the generalization of these rules to more complex CH cases. The other reasoning path focuses on inductive knowledge, applying graph analytics to generalize insights from accumulated data. Given the complexity of CH buildings and the inherent sparsity of data, a combined approach may provide the most robust solution.

In the context of the entire building lifecycle, the integration of diagnostic data with maintenance actions provides the opportunity to model the current condition, the expected degradation patterns and the corresponding interventions required over time. Such a broader perspective places structural diagnostics knowledge management into the facility management research agenda for CH buildings. One promising area of research to consolidate is the combined use of the two established ontological frameworks, IFC schema and CIDOC CRM, for managing both the technical and cultural aspects of CH building maintenance.

Ultimately, research prospects tied to this approach have the potential to enhance the preservation of CH works by aligning diagnostic data with actionable maintenance and restoration workflows, ensuring the longevity of heritage structures while maintaining their cultural significance.

CRediT authorship contribution statement

Antoine Gros: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Livio De Luca:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization. **Frédéric Dubois:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Philippe Véron:** Supervision, Project administration, Funding acquisition, Conceptualization. **Kévin Jacquot:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

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