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A Knowledge Graph Based Common Data Environment Solution for Building Seismic Loss Estimation

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Abstract

Seismic Loss Estimation (SLE) has become a critical aspect of modern building engineering, aiding in mitigation strategies, real-time disaster response, and post-earthquake reconstruction. The FEMA P-58 method, a performance-based earthquake engineering tool, efficiently links component damage states with engineering demand parameters for comprehensive seismic loss assessment. However, managing the extensive data and semantics required for such evaluations poses challenges. This paper proposes a Knowledge Graph (KG)-based solution, integrating object-based information management principles akin to Common Data Environment (CDE) and Building Information Modeling (BIM). By leveraging KG and digital twin technologies, this approach aims to facilitate dynamic seismic loss estimation, providing stakeholders with a comprehensive view of building performance and enabling efficient data access and analysis.

1 Introduction

In modern building engineering practices, seismic loss estimation (SLE) has gradually become an important part across the different stages of buildings. In pre-earthquake stage, such procedure is useful for adopting suitable mitigation strategies or structural designs; during the earthquake event, it can facilitate the decision making for real-time disaster response and relief efforts; after an earthquake event, it can become a good criterion for reconstruction and rehabilitation (Shi et al., 2023; Xu et al., 2019). In the last few years, performance-based earthquake engineering approaches have been proposed to evaluate the performance of certain structures under seismic excitations. Among them, the FEMA P-58 method, a recent product of performance-based earthquake engineering, stands out for its capability to perform fine-grained, full-term seismic loss estimation (ATC, 2012). Its specialty is the capability to efficiently connect the damage state of the component combinations (performance groups, PGs) with specific engineering demand parameters (i.e., peak inter-story drift ratio PIDR, peak floor acceleration PFA). The FEMA P-58 method has been proven to be effective for diverse structural types, including masonry (Zeng et al., 2016), reinforced concrete frame (Baradaran et al., 2013, Del Vecchio et al., 2018, Shi et al., 2023), steel frame with seismic force-resisting systems (Del Gobbo et al., 2018, Yang & Mutphy, 2015).

Such applications require an abundance of data regarding the building of interest, such as the decomposition of different building subsystems, real-time measurements of specific physical quantities, detailed information of both structural and non-structural components, especially for their fragility against specific seismic impacts. Additionally, to effectively impart the building performance to different stakeholders, semantics regarding the seismic loss estimation may need to be further supplemented by the relevant material, such as technical reports or regulatory documents. Moreover, multiple models will be set during the analysis procedure of building seismic loss estimation. The integration of these analytical results is also helpful for the decision makers to have a comprehensive view of the target asset. Despite the wealthiness, challenges occur in managing the relevant data and exploring the underlying semantics. It spawns demand for developing an effective data management environment to make the involved information easy to access and exploit.

In the history of information management for urban assets, including buildings and civil engineering works, common data environment (CDE) and building information modeling (BIM) are two intertwined fundamental concepts. Specifically, according to ISO 19650-1 2018 (ISO, 2018), CDE refers to agreed source of information for any given project or asset, for collecting, managing and disseminating each information container through a managed process. Meanwhile, BIM is the use of a shared digital representation of a built asset to facilitate design, construction and operation processes to form a reliable basis for decisions. In our humble perspective, as illustrated in **Figure 1**, one of the important common idea underlying these two concepts is the object-based information management paradigm. The kernel of object-based information management paradigm for the built assets is to regard the involved object hierarchy (buildings, building subsystems, components) as the backbone of the relevant information collected from multiple sources. Information such as that within technical reports, real-time measurements from the corresponding sensor networks are required to be integrated to specific objects of interest so that the stakeholders can explore the embedded semantics freely with object-based query engine.

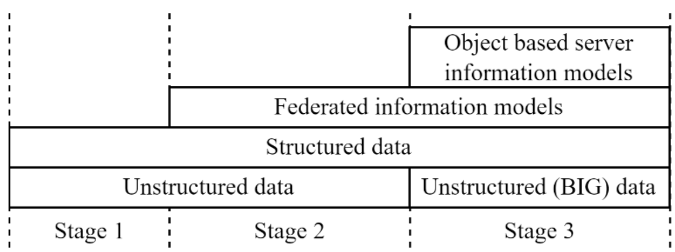

Figure 1: A perspective on stages of maturity of analogue and digital information management: Information Layer (Adapted from ISO 19650-1).

Similar ideas are also introduced by knowledge graph (KG) and digital twin technologies. In 2012, the famous blog posted by Google entitled “Things, not strings” revealed the essence of knowledge graph as managing the relevant data with object-based paradigms. It proposed a web with semantics which reveals real-world entity interconnections, thereby enabling applications across multiple scenarios, including intelligent search, question and answer (Q&A) systems, personalized recommendation services. Knowledge graph allows users to explore the connections between entities of interest and their potential neighbors, thus broadening their knowledge horizons. Similarly, digital twin technologies, originally proposed for constructing mirrored digital representations for aircrafts, emphasized the importance of object-based information management for different level of details. In such context, information and status of the components from the different levels of system decomposition are integrated and reflected accordingly.

To this end, this paper proposes a KG-based object-based common data environment solution for dynamic seismic hazard assessment based on previous work and the specific data requirements of building seismic loss estimation tasks.

2 METHOD

2.1 KG-based CDE for building seismic loss estimation

In the context of building seismic loss estimation, conventional building information management may encounter three significant challenges: 1) representation of status history of buildings and their corresponding components under seismic events; 2) articulation of the underlying relations between the state of a complex object and the state of its components at various compositional levels, and 3) integration of heterogeneous data from multiple sources related to such applications. These three challenges correspond to three important information management requirements in the application of building seismic loss estimation. The proposed data model, hence, ultimately needs to be flexible enough to satisfy these requirements.

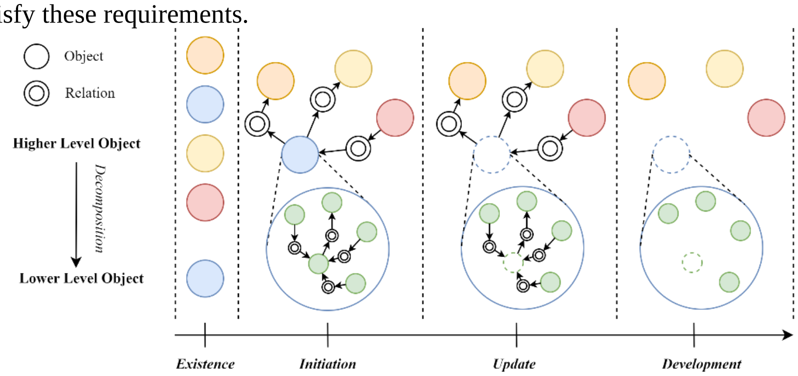

Figure 2: Schematics of cascading failures of interconnected components in a hierarchical system.

It is acknowledged that each object may possess multiple attributes and states, which can be subject to change over time. Illustrative examples of this phenomenon include the position of an object at different moments in time or the progression of structural damage in a building throughout an earthquake event. The information requirements for the attributes and states of the involved objects vary across different application scenarios and must be adapted to meet specific needs. In addition to attributes and states, the relationship between objects may also change over time, e.g., some dependent subsystem components may not be able to maintain normal functional connections with each other due to the failure of a component. As shown in Figure 2, insufficient redundancy or failure of key components of a system sometimes may lead to cascading failures, resulting in system-level functional paralysis and significant losses, such as the famous cascading failure of the Italian power grid reported by Buldyrev et al., 2010 and the cascading collapse of structures.

In the case of a complex object, it is possible that some of its properties and states may be jointly determined by the states of its various components. These components can be regarded as some kind of functional relationship. The state of a building, as a complex object, is constrained by the states of its various components. For instance, in the context of an earthquake, the damage state of each building in the region constitutes a pivotal basis for emergency relief decision-making, with the overall state of the building reflected by the damage state of each floor, which in turn is reflected by the damage state of its associated structural components. Subsequent to the earthquake, the estimation of the overall loss to the building, in this case, is primarily determined by the loss of each component, including both structural and nonstructural components.

Relying on a single data source is commonly inadequate to accurately describe a building and its components to different stakeholders. It is also a complicated task to obtain the required information from the CDE for different analytical purposes. For the building seismic damage assessment scenario based on performance analysis, the semantics of describing a column object includes not only the location, such as the floor to which it belongs, and the connectivity of its components, but also its mechanical properties, structural conditions, constraints, ideal representations (refined or simplified representation of the element for structural analysis), the performance group to which it belongs and its corresponding fragility group, the meanings of the indicators describing the current damage state, the value of the performance indicators corresponding to different damage states. The semantics of these properties are usually stored implicitly in the information model and need to be described by domain knowledge from different knowledge sources. Therefore, how to effectively manage these heterogeneous knowledge sources is another practical issue to be considered in similar real-world application scenarios of building information.

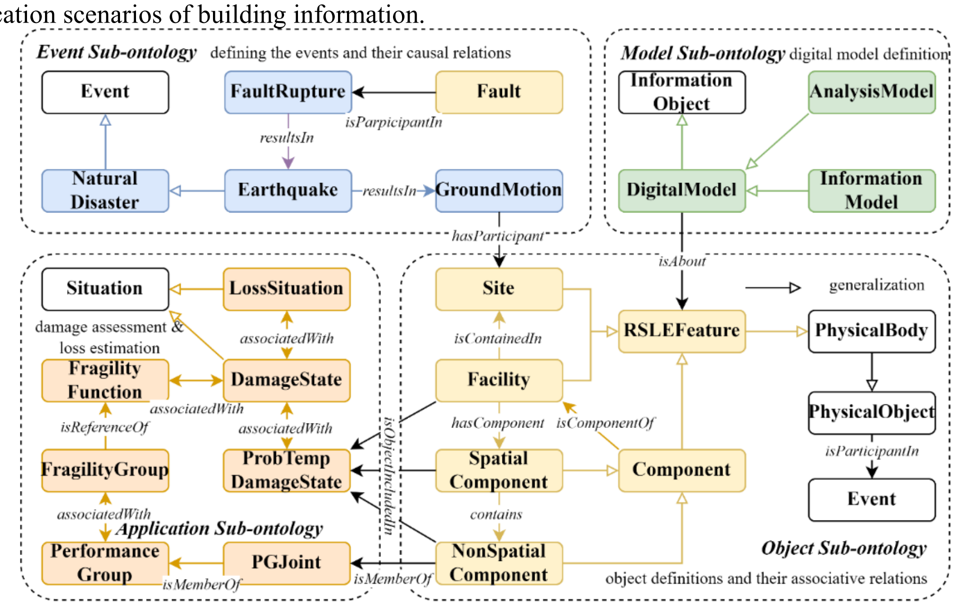

Figure 3: Dynamic regional seismic loss estimation ontology (DRSLEO) proposed in our previous study (Pan et al., 2024).

In our previous study, we have proposed a new domain ontology called dynamic regional seismic loss estimation ontology, DRSLEO in short. It has been established upon the concepts from FEMA P-58 and knowledge organization experiences from multiple outstanding outcomes of knowledge engineering, including a descriptive ontology for linguistic and cognitive engineering DOLCE (Borgo et al., 2021), industry foundation classes IFC (ISO, 2018), building topology ontology BoT (Janowicz et al, 2020). DRSLEO is still a developing ontology and was initially presented to formalize the relevant concepts and relationships within the field of seismic loss estimation.

Figure 3 illustrates the main structure of this ontology. It is composed of four conceptual parts, including event, object, model, and application sub-ontologies. The "event" sub-ontology maintains concepts for defining events and their causal relations, the "object" sub-ontology maintains those for defining objects and different kinds of associative relationships, the "model" sub-ontology maintains those for defining digital models and some other information objects, the “application” sub-ontology maintains those for states or situations that reflect the status of the objects of interest. In this section, details are given about how the knowledge-graph-based CDE can be used to specify the objects of interest and their interactions with their digital representations for respective purposes.

In information science, the term “ontology” is widely accepted as a conceptual representation of the domain of interest. It excels at conceptualizing the interconnections between different concepts. It is also a kind of data model that can be used to organize the data involved by the specific tasks of this application in a logical way. A well-established ontology is regarded as a logical foundation for reasoning upon the instantiated facts. As shown in Figure 4, we adopt DRSLEO to the data integration procedure in forming a knowledge graph based common data environment.

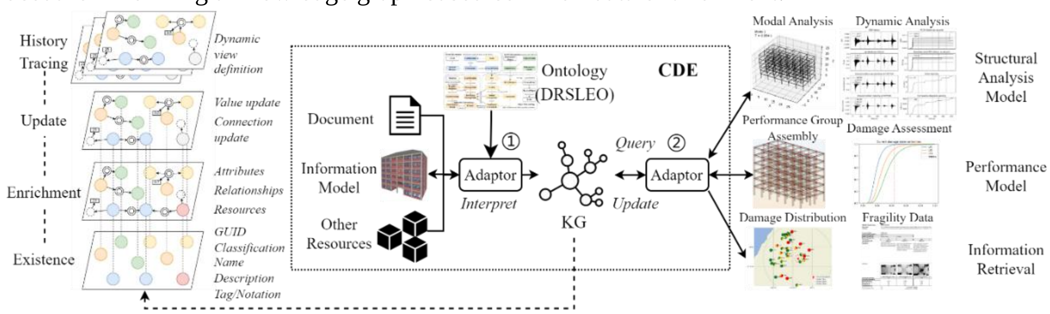

Figure 4: Illustration for the construction and implementation of the proposed knowledge graph (KG) based common data environment (CDE) for building seismic loss estimation.

As shown on the left of Figure 4, to begin with, objects and events involved in this application are identified and classified according to the data requirements of performance-based seismic loss estimation. They are further semantically enriched with the information selectively extracted from both structured and unstructured data (e.g., fragility database, specifications for structural analysis and fragility analysis, document regarding the asset and its sub-systems, ground motion database) and progressively organized into the corresponding knowledge graph. The corresponding knowledge graph in this stage serves as a base graph which reflects the initial state of the target asset. Upon this, update actions may be recalled with additive modifications to the base graph to reflect the status of the asset and its involved components. Each status should be assigned with a timestamp that is crucial to be queried with the specific time or duration of interest. The status of an object may be described by the combination of the valued indicators (e.g., peak inter-story drift ratio) or the existence of specific connections between the individuals, such as the functional relationships between a structural joint and its relevant structural components. Therefore, it is necessary to conserve the modification history as the value or relation regarding the object changes. The retrieved subgraphs for different update time instants can be seen as snapshots of the object during the different stages of the asset. As a result, they together form a dynamic view of asset status.

The first adaptor presented in Figure 4, hence, is responsible for extracting the essential data from multiple data sources and aligning them under the guidance of the corresponding ontological structure. In this procedure, objects of interest are identified and further semantically enriched with their attributes, status, constraints, correlations to other objects. Both structured and unstructured data are selectively passed through this interpretation process. For efficiency, not all data are fragmented into tiny data pieces so that they can be embarrassingly embedded into the corresponding knowledge graph. Reference mechanisms are adopted to address this issue. In one case, part of the semantics of the object of interest is already maintained by another accessible data source, such as, formal description of the classification of a specific object from an organized classification system. In another case, although images and videos regarding the object of interest are indispensable resources to represent the current and historical status of the object, they are not directly stored while referenced in this knowledge graph.

The other adaptor is to deliver the required information for different tasks, such as allocation of structural analysis model and performance model. The analytical results are written back to the knowledge graph through the adaptor once the analysis is completed. There is another task for common information retrieval or object status exploration. In this study, resource description framework (RDF) and the corresponding query language (SPARQL Protocol and RDF Query Language, SPARQL) for organize and manipulate the information of the knowledge graphs. Since the data requirements of the downstream tasks vary, details will be given in the following sections.

Prior to elucidating the construction of the proposed CDE, there is another important concept to delineate further, namely, “object”. An object in this context refers to a thing that is identifiable and capable of describing with a bunch of attributes. The definition of “object” in this context is much narrower than that in IFC, where it refers to the generalization of any semantically thing or process. It is close to “Endurant” in DOLCE’s context. Things such as events and processes are formally defined by other concepts. As the definition implies, the most fundamental attribute is to be identified as an individual and can be described by supplementary information. Each individual that needs to be identified in this context should be associated with a globally unique identifier (GUID), which is also emphasized by IFC. They include physically tangible items such as wall, beam or covering, physically existing items such as room, storey, building. Practically, a fixed 22-character style GUID, suggested by buildingSMART (buildingSMART, 2024), is adopted in this study. It can be created through a reversible transformation of a universally unique identifier (UUID), which is a most frequently used identifier generated by the algorithm of UUIDv4 defined by the specification of RFC 4122.

2.2 Construction of the knowledge graph

As shown in Figure 2 and Figure 4, each knowledge graph can be seen as a web with semantics which reveals entity interconnections. With the convention of RDF, the graph consists of a series of triplets in the form of (subject, predicate, object). Each triplet is a fact or, more formally, statement regarding the knowledge graph. OWL 2 Web Ontology Language is a formal ontology language for the Semantic Web (Motik et al., 2012). It defines formal representation of the triplet components can be described. In such context, subject should be an individual, either named or anonymous; an object can be either an individual or a specific data value; a predicate, hence, can be regarded as object property when it connects two individuals, data property when it connects the individual with its attribute values, or annotation property when it is used to provide an annotation assertion of the individual, such as providing human-readable label or comment. Both named and anonymous individuals are regarded as nodes in the knowledge graph. Named individuals are those with globally unique identifiers, while anonymous individuals are not needed to be uniquely identified.

Compared to the wide usage of identifier within IFC schema, we narrowed the identifiable features to limited objects in this corresponding task. The criterion is that only the objects required to be frequently queried or referenced by the other individuals, such as wall, beam, column, storey, are named individuals, otherwise, they are treated as anonymous individuals, sometimes, also called blank node in the sense of graph structure. Upon the named individual, for descriptive capacity, each base individual in this task needs to be described with the other intrinsic attributes, such as name, description, tag, notation, and classification, as shown in Table 1. Unlike the GUID, these kinds of attributes are more human-readable, and suitable for indexing the corresponding individuals for query. This procedure is named “existence” definition in this study, as shown in Figure 4. The semantics of the individual can be complemented with its associated classification system outside the knowledge graph if it is possible to access with integrated query.

Individual type	Prototype	Attribute	Description	Restraint
BaseIndividual	NamedIndividual	id	Unique identifier for the individual	Automatically generated
		name	Name of the individual	Optional[str]
		description	Description of the individual	Optional[str]
		tag	Tag of the individual	Optional[str]
		notation	Notation of the individual	Optional[str]
		classification	Class of the individual in an existing classification system	Optional[str]
		_type	Class of the individual defined in the ontology	str
		_namespace	Namespace that the individual belongs to	Namespace IRI
BaseBlankNode	AnonymousIndividual	name	Name of the individual	Optional[str]
		description	Description of the individual	Optional[str]
		_type	Class of the individual defined in the ontology	str

Table 1: Attribute declaration of BaseIndividual and BaseBlankNode.

Based on these two fundamental concepts, domain-specific concepts proposed in DRSLEO are then extended accordingly. Inspired by BoT and IFC, a built asset is decomposed into several spatial components (e.g., storey, room, zone) and nonspatial components (e.g., structural components, nonstructural components). The built asset can be somehow classified as different types according to different classification systems. However, in ontological definition, it can be only classified as limited types that have similar attributes in common. The decomposition of building subsystems can be extracted from the corresponding information models easily, although the maturity of information about the involved subsystems varies from stage to stage.

With regard to their components, apart from the existence definition, each component type can have its specific attributes or associative relationships. They are essential for constructing a structural analysis model or performance model. For example, mass distribution strongly affects dead load distribution as well as the structural behavior under dynamic excitations. Therefore, the density and dimension of each tangible object will be calculated or at least estimated when it is declared as a component of the built asset. Other information that helps to enrich a component's semantics in this task includes its location, geometric representation (e.g., body representation or axis representation) and its association with the other components (e.g., decomposition, connectivity, assignment).

Among the associative relationships, connectivity is one of the most important. Connectivity mentioned here is either regarding relationship between components that are physically connected or functionally connected. IFC treats a relationship that describes the spatially containment as a kind of connectivity. Such connectivity is essential for defining the loading path of a structural system from each storey above to the ground. It is also important information for us to determine the performance groups relating to each storey since some fragility groups of the structural components are categorized by structural joints, such as beam-column joints. To be noticed, the extracted information by the adaptor forms an intricate interconnected web structure before it is converted into a graph structure. Once the information is collected, the instantiation of the knowledge graph of the asset of interest is conducted recursively from one individual to its associated individuals, as shown in the following pseudo code. However, such recursive individual instantiation procedure is prone to cyclic references since the recursion will not stop until stack overflows. Therefore, when organizing the extracted information from the information models and other information sources, it is necessary to make sure the associative relations form an acyclic directed graph.

Algorithm 1 Recursive individual instantiation (with rdflib library and Python programming language)

```
Input: individual: an object that holds information extracted from multiple data sources
       graph: an RDF graph used for representing the asset of interest
Output: iri: an international reference identifier (IRI) for
function ToRDF(individual, graph):
    this ← individual.iri
    if not getattr(individual, “is_declared_in_rdf”) then
        super(individual).ToRDF(graph)
        graph.add((this, RDF.type, DRSLEO[individual.type]))    # class declaration
        graph.add((this, DRSLEO[“globalId”], Literal(individual.id)))    # guid
        if getattr(individual, “name”) then
            graph.add((this, SKOS.prefLabel, Literal(individual.name)))
        end if
        if getattr(individual, “description”) then
            graph.add((this, RDFS.comment, Literal(individual.description)))
        end if
        graph.add((this, RDFS.comment, Literal(individual.tostr()))
        # declarations for other attributes, case by case, omitted
        # declarations for associative relations, here we demonstrate the connectivity relation
        for other_individual ∈ individual.connects_to.values() do
            other_iri ← other_individual.ToRDF(graph)
            graph.add((this, DRSLEO[“connectsTo”], other_iri))
            graph.add((other_iri, DRSLEO[“connectsTo”], this))
        end for
        # other relations
        setattr(individual, “is_declared_in_rdf”, True)
    return this
end function
```

3 Results

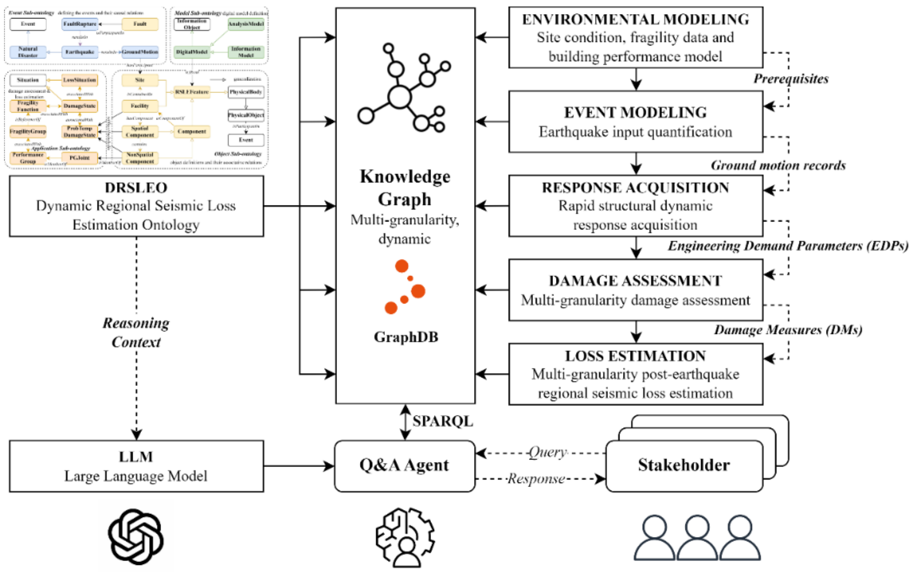

Figure 5: An overview of the workflow of semantic-augmented FEMA P-58 based DRSLE.

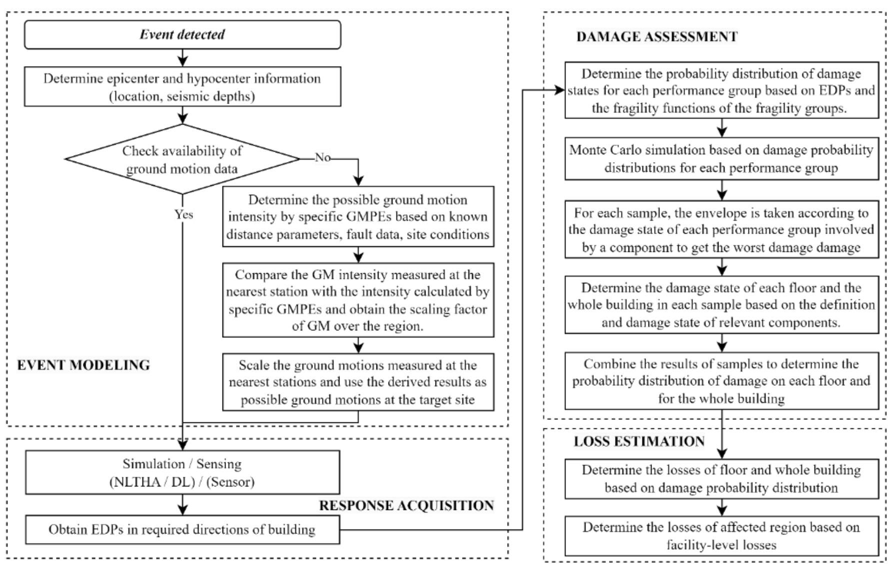

Figure 6: Specification of event modeling, response acquisition, damage assessment, loss estimation in RSLE.

Figure 5 and Figure 6 illustrate the five-step workflow of the dynamic regional seismic loss estimation based on FEMA P-58 and DRSLEO, which encompasses a) environmental modeling (site condition, fragility database, building performance model, etc.); b) event modeling (epicentral location, depths, fault type, rupture plane information, recorded or derived ground motions); c) response acquisition (simulation or sensing); d) damage assessment (Monte Carlo simulation upon the performance groups with EDPs and the fragility functions of their relevant fragility groups); and finally

e) loss estimation (multi-granularity estimation for various loss measures based on the damage assessment results). DRSLEO, serving as a unified schema, provides a standardized approach for retrieving both static and dynamic data generated throughout this entire process. During the interaction procedure between the stakeholders with different roles and the bespoke LLM-empowered Q&A agent for DRSLE, the DRSLEO further provides schematic contexts for the exploration of the corresponding knowledge graphs of the relevant information.

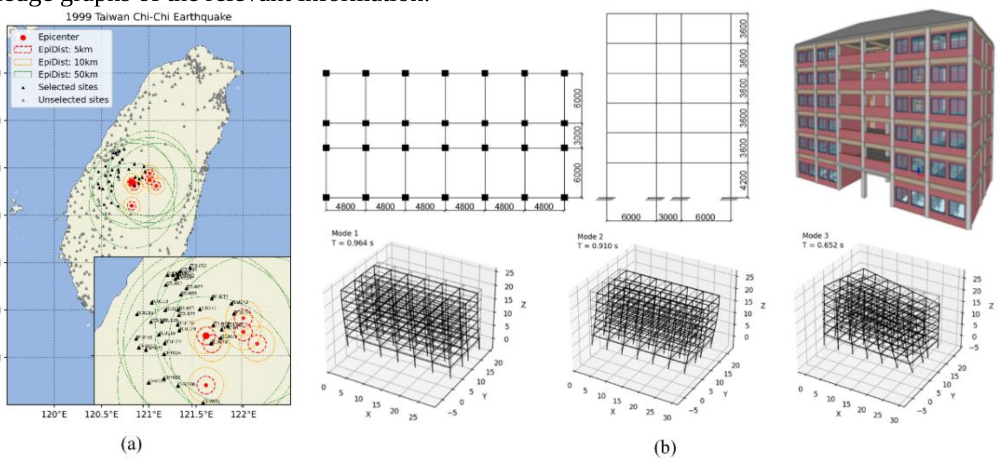

Figure 7: (a) epicentral information and influence circles of mainshock-aftershock sequence of 1999 Chi-Chi earthquake, and distribution of selected and unselected stations in this case study; (b) configuration of the 6-storey RC-OMF educational building (T_1 is 0.964s, T_2 is 0.910s, T_3 is 0.652s).

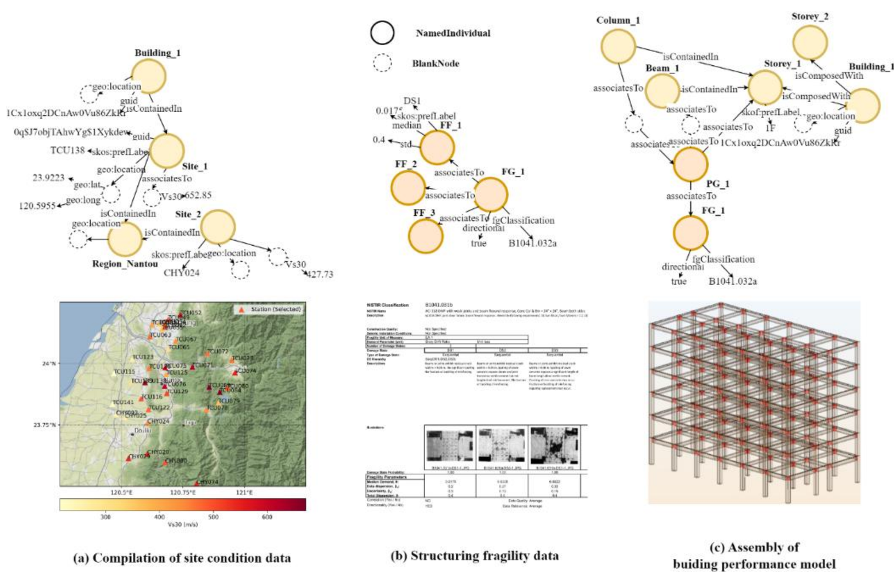

Figure 8: Graph representation for relevant data in environmental modeling

This scenario is set in 1999 Chi-Chi earthquake event. Ground motion records pertinent to this event have been extracted from the PEER NGA West2 database. The selection of this seismic event is based on two key factors. Firstly, Taiwan had established an extensive seismograph station network prior to the disaster, providing access to a considerable number of ground motion records (over 400 stations) with the majority containing three-dimensional ground motion data. This wealth of data renders it suitable for validating the ontological model's capability to accurately represent the spatial distribution of the loss estimation within the affected region. Secondly, the 1999 Chi-Chi earthquake was followed by non-trivial aftershocks, which makes it an ideal candidate for evaluating the ontological model's capacity to capture the temporal evolution of dynamic seismic loss estimation.

Given the impact of the event, 38 sites in the Nantou seismic region have been selected for detailed analysis. Figure 7 (a) describes the epicentral information, influence circles of this mainshock-aftershock sequential event and the spatial distribution of both selected and unselected stations for this study. The scattered epicenters of Chi-Chi earthquake sequence suggest that any structure in the area could potentially experience aftershock ground motions as intense as or even stronger than the mainshock, depending on the specific site conditions and seismic wave propagation effects. To assess the regional distribution of damage and track the progression of structural damage caused by the mainshock-aftershock sequence of the Chi-Chi earthquake, each site is sampled a few ideal frame structures with the construction of the corresponding knowledge graph for each asset. In more practical cases, this sampling procedure may be enhanced by the actual status of the real assets. The environmental information, such as site conditions, and data form fragility database are organized as shown in Figure 8. Figure 8 also depicts the basic interaction between the performance group, fragility group, and the building components of the asset.

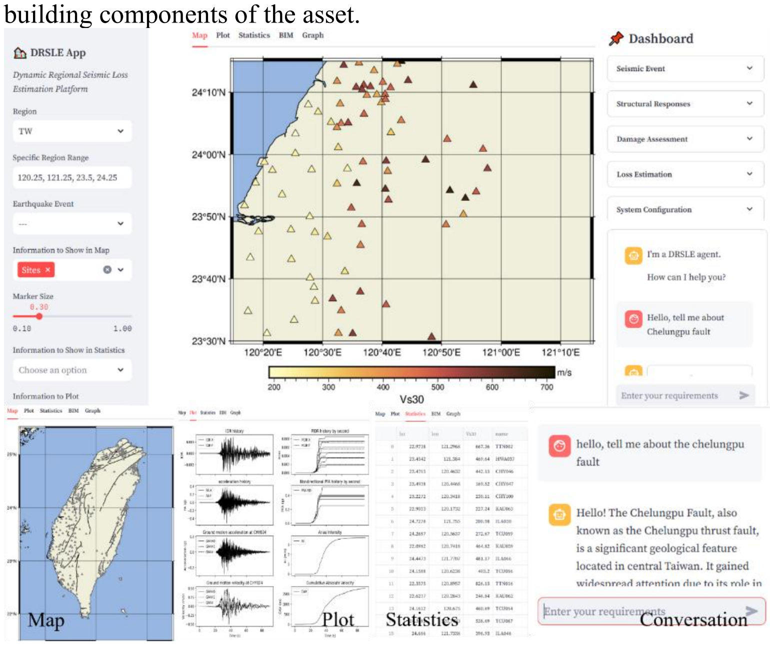

Figure 9: An overview of the prototype workbench for semantic-augmented FEMA P-58 based DRSLE.

4 Conslusions

This research has identified and addressed three critical challenges in the data management of building seismic damage assessment: 1) representation of status history of buildings and their corresponding components under seismic events; 2) articulation of the underlying relations between the state of a complex object and the state of its components at various compositional levels, and 3) integration of heterogeneous data from multiple sources related to such applications. The proposed object-oriented CDE and knowledge graph-based solution aim to provide the necessary flexibility and integration capabilities to tackle these challenges effectively.

While the FEMA P-58 guidelines offer a solid foundation, the proposed approach extends its capabilities by incorporating real-time field data and object state assessments, thereby enhancing the comprehensiveness of seismic loss estimation. The integration of diverse data sources through an object-based framework allows for a more nuanced understanding of building performance during seismic events, facilitating informed decision-making for emergency response and reconstruction efforts.

Nevertheless, the current solution acknowledges the complexity of real-world building systems and the influence of functional components and subsystems on seismic damage assessment. Future work will focus on further refining the data model to capture these intricacies, ensuring a more accurate reflection of building behavior.

In summary, the integration of knowledge graph technology within an object-oriented CDE presents a promising avenue for advancing seismic damage assessment practices. By improving data management and facilitating knowledge discovery, this approach lays the groundwork for more resilient and informed building engineering in the face of seismic hazards.

Acknowledgements

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