WORLD CONFERENCE ON TIMBER ENGINEERING 2025
BRISBANE, AUSTRALIA

Advancing Timber for the Future Built Environment

DIGITAL TWINNING FOR ENHANCING TRANSPARENCY IN SUSTAINABILITY, SAFETY, HEALTH AND SERVICEABILITY OF TALL TIMBER STRUCTURES

Noémi Friedman[1], Blaž Kurent[2], Bence Popovics[1], Stevan Nesović[3], Branimir Rakić[3], Gregor Karlovsek[3], Ema Lovsin[3], Nenad Milosevic[4], Igor Osmokrovic[4], Katja Malovrh Rebec[5], Rok Rudolf[5], Boštjan Brank[2]

ABSTRACT: Digital twin technology has recently emerged as a transformative approach in building management, enhancing transparency, sustainability, safety, health, and comfort. This paper explores how the European HORIZON project BUILDCHAIN leverages this technology to promote the use of timber as a viable material even for taller buildings, emphasizing its sustainability benefits and improving its safety and serviceability metrics. The BUILDCHAIN project integrates diverse data sources, including 4D, 5D, and 6D Building Information Models (BIM), Finite Element (FE) models, and real-time sensor data, to create dynamic, real-time virtual replicas of physical buildings. These digital twins provide a comprehensive and accessible view of building properties and performance, facilitating continuous monitoring and updating of FE models based on real-world data to ensure ongoing structural health and safety. Through the case study of two tall buildings made of CLT panels, we demonstrate the practical application of this technology and discuss how integrating data from multiple buildings can refine and re-evaluate existing design procedures and standards. This offers a new paradigm in building design validation. By enhancing transparency and incorporating advanced monitoring capabilities, the BUILDCHAIN project paves the way for more resilient, efficient, and sustainable building practices.

KEYWORDS: Tall Timber Buildings , Inverse Methods , Digital Twin , Model updating , DKG

1 – INTRODUCTION

Timber is increasingly recognized as a sustainable and renewable material for tall buildings, aligning with global efforts to reduce environmental impact in construction. While it offers significant advantages – such as a lower carbon footprint and renewability – ists use in high-rise structures still faces adoption challenges. Providing accurate digital information on the as-built properties and performance of timber buildings can enhance tranparency and build confidence in this material. It also offers oppoprtunities to refine standardized design procedures, especially when discrepancies arise between expected and actual building behavior. Improving these procedures can help boost key performance metrics related to structural integrity, safety, and serviceability—critical factors for architects, engineers, and regulatory bodies. Demonstrating timber's capabilities through real-world performance data is a great way to promote its acceptance and build trust within the construction industry.

Tall timber buildings can exhibit unexpected vibrational behavior under dynamic loads like wind and seismic activity, often diverging from engineering predictions. Bayesian inference has evolved into a powerful statistical tool for inferring design parameters in simulation models, and by that updating the model of the structure, using non-destructive tests such as forced vibration tests conducted on as-built structures [11, 12]. However, challenges can arise within the Bayesian framework due to persistent systematic errors in simulation models. These errors often stem from simplifications made when translating complex, real-world conditions into numerical representations. Even with the incorporation of stochastic elements to account for uncertainties, the updating process may introduce systematic biases that compensate for unknown factors. While this typically leads to a better match with observed building behavior, it can distort the original physics-based parameters and reduce the generalizability of the model. To address this, we propose a novel and robust framework that accurately identifies design and modeling parameters by integrating digital twin models from multiple structures that share common parameters representing the same physical properties.

Engineers, however, typically do not have access to measurements from buildings that share the physical properties of interest. In many cases, even engineers who designed a spedific building structure do not have access to measure-

[1]AI Laboratory, HUN-REN Institute for Scientific Computing and Control (SZTAKI), Budapest, Hungary, n.friedman@ilab.sztaki.hu
[2]Faculty of Civil and Geodetic Engineering, University of Ljubljana, Ljubljana, Slovenia, bbrank@fgg.uni-lj.si
[3]Trace Labs (OriginTrail Core Developers), Ljubljana, Slovenia, branimir.rakic@origin-trail.com
[4]BEXEL Manager, Belgrade, Serbia, nenad.milosevic@bexelconsulting.com
[5]Laboratory for Building Physics, National Building and Civil Engineering Institute (ZAG) ,rok.rudolf@zag.si

https://doi.org/10.52202/080513-0276

ments taken on that very structure. To make a follow-up procedure feasible, a platform where all type of digital information related to a building – such as measurements and digital twins – can be discovered and shared – when permitted by users, is essential. The BUILDCHAIN project's Digital Knowledge Graph (DKG) system [2, 5] (learn more about the European Commisision-funded project at https://buildchain-project.eu/) plays a key role in supporting follow-up procedures to identify discrepancies between as-designed and as-built performance metrics. In particular, the DKG supports the proposed multi-building approach by making experimental data from various structures both discoverable and accessible. Acting as a secure and validated repository, it offers researchers, engineers and standardization bodies access to trusted and reliable data. By integrating information across multiple buildings, the system enables the application of probabilistic methods to refine and update design parameters, thereby enhancing predictive accuracy. This approach not only supports the safety, serviceability, and structural integrity of individual buildings but also contributes generalized insights to improve future design standards and procedures.

The second key enabler of the proposed multi-building updating framework is the mathematical formulation of a joint updating procedure, that links shared parameters across multiple building models. This formulation, developed in this paper, allows for integrated parameter refinement using data from different structures.

The demonstrate this, the remainder of this paper is structured as follows. Sec. 2 presents the methodology, beginning in Sec. 2.1 with the role of the BUILDCHAIN system to support digital twinning by creating structured, traceable, discoverable and transparent building data via a Decentralized Knowledge Graph (DKG) system and building related ontologies. Section 2.2 introduces digital twin technology, explaining the probabilistic process of updating model parameters using measurements of the behavior of a single structure. Expanding on this, Sec. 2.3 proposes a novel joint updating framework that leverages multiple building datasets to refine structural models and improve predictive accuracy. Section 3 applies this methodology to tall timber buildings, illustrating how data on these structures can be accessed through the BUILDCHAIN platform using two case study buildings. It then introduces the joint Bayesian updating approach for these two buildings, demonstrating how measurement data from multiple buildings enhance model parameter refinement and improve predictive accuracy. Finally, Sec.4 summarizes the findings and discusses the broader implications of integrating digital twin technology with multi-model Bayesian updating. The paper concludes by reflecting on how this approach enhances the reliability of timber-based construction, informs future design practices, and contributes to the wider adoption of sustainable high-rise timber buildings.

2 – METHODOLOGY

2.1 KNOWLEDGE GRAPH FOR TRANSPARENT BUILDING INFORMATION

Digital Building Logbook Digital Building Logbooks (DBLs) serve as repositories for storing essential building data, from administrative records to performance metrics. By digitizing building-related information, DBLs enhance information management and facilitate more informed decision-making across the entire building lifecycle. Their impact includes real-time monitoring, operational optimization, and improved sustainability in the Architecture, Engineering, and Construction (AEC) industry, offering a trusted, single point of access to verified building data. Recognizing their importance, policymakers, public authorities, and enterprises have increasingly supported DBL initiatives, leading to multiple pilot projects and developments [7, 8, 14, 19]. A European Commission study concluded in October 2023 provided an EU-wide semantic data model and technical guidelines for DBL implementation, aiming to create a network of interoperable national platforms connected via a European portal [3].

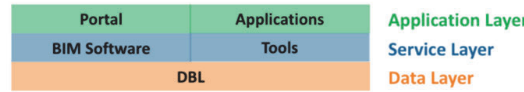

Figure 1: BUILDCHAIN architecture

The rough architecture of the BUILDCHAIN DBL system is illustrated in Figure 1, depicting its three primary layers. At the foundation, the data layer stores and organizes essential building-related information. The middle layer integrates the in-built BEXEL BIM management software alongside various tools and services that facilitate data processing and analysis. The top application layer provides multiple APIs for diverse functionalities and serves as the interface for the main BUILDCHAIN UI, ensuring seamless user interaction and accessibility. Among the available APIS is one specifically designed to enable the digital twinning procedures described in this paper. It supports model updating for both, structural health monitoring keeping in track with changes of material properties and the enhancement of design procedures using measurements data from single or multiple buildings.

Discoverability via structured building data In the BUILDCHAIN DBL system, the data layer is organized into Knowledge Graphs, which provide an organized representation of real-world entities and their interconnections. Knowledge Graphs facilitate the integration of diverse data sources, ensuring that information is both accessible and contextually meaningful. By leveraging building-related ontologies and semantic relationships, these graphs enhance advanced querying, automated reasoning, and intelligent decision support in construction management [17, 18].

A significant portion of building-related data is inherently structured within Building Information Modeling (BIM) frameworks, which employ standardized, interoperable schemas such as Industry Foundation Classes (IFC), BRICK, and SAFRAN. IFC, in particular, serves as a crucial open standard for enabling seamless data exchange across various stakeholders and software platforms in the Architecture, Engineering, and Construction (AEC) industry. By structuring as much information as possible within the IFC framework, we ensure high interoperability and

https://doi.org/10.52202/080513-0276

longevity of data within the construction ecosystem.

BIM extends beyond traditional 3D modeling to incorporate additional dimensions of data that enhance project planning and lifecycle management. 4D BIM integrates time-related information, enabling improved scheduling and visualization of construction sequences. 5D BIM incorporates cost estimation, linking financial data with the project timeline and model elements. 6D BIM extends this further by including sustainability and facility management data, allowing for better decision-making regarding energy efficiency, maintenance, and long-term asset performance.

However, some data types do not natively fit into IFC or similar BIM schemas. Examples include complex simulation models, compliance documentation, design standards reports, and performance assessment records. For such data, a careful and structured approach to ontology definition is required. These ontologies should be designed to complement IFC and other BIM standards, ensuring that external datasets remain interoperable while enhancing data discoverability, mining capabilities, and decision-making processes. By aligning non-IFC data with well-defined ontological structures, we maximize the potential for cross-platform compatibility and integration within the broader construction knowledge ecosystem.

Decentralized Knolwedge Graph technology A DKG is a distributed data structure that combines the advantages of knowledge graphs and blockchain. It enables structured data representation while maintaining security, accessibility, and trust. OriginTrail Decentralized Knowledge Graph presents a global, open data structure composed of interlinked Knowledge Assets structured in a Resource Description Framework (RDF) knowledge graph hosted on an open, permissionless decentralized network of Decentralized Knowledge Graph nodes. [18]

The Decentralized Knowledge Graph consists of three layers. The Decentralized Knowledge Graph layer stores the knowledge graph data, distributed across the network in separate graph database instances. The blockchain layer interfaces with various blockchains, such as NeuroWeb on Polkadot, Base, and Gnosis to manage node relations and implement trustless protocols. Lastly, the application layer includes both Artificial Intelligence (AI) driven and traditional applications that use the OriginTrail Decentralized Knowledge Graph in their data processes. OriginTrail Decentralized Knowledge Graph architecture is presented in Figure 2.

The Decentralized Knowledge Graph (DKG) supports both, public and private knowledge. The public graph is replicated across all network nodes, allowing data discoverability through a decentralized index and enabling search queries. Private graphs are hosted by individual nodes and connected to the public graph. Once information is discovered in private graphs, data exchange protocols, like a data marketplace protocol, facilitate data retrieval.

The protocol actors in the OriginTrail Decentralized Knowledge Graph (DKG) consist of knowledge publishers, who publish knowledge; data holders that help uphold the DKG and are incentivized with tokens; and knowledge users, who query and utilize the knowledge. Both knowledge publishers and knowledge users can be humans or AI agents, enabling a more dynamic and intelligent exchange of information within the network.

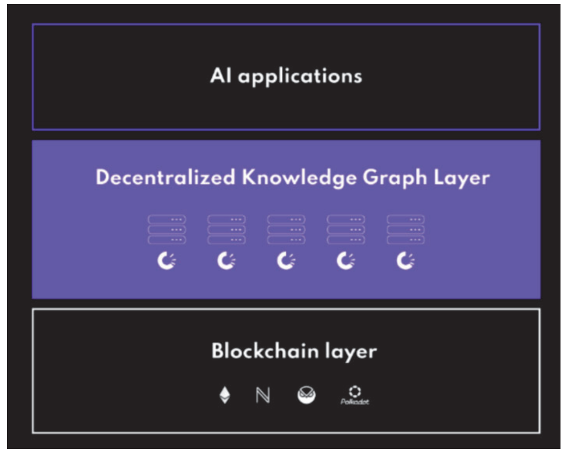

Figure 2: DKG Architecture

Blockchain technology and smart contracts for traceability Datasets published to the Decentralized Knowledge Graph (DKG) are called Knowledge Assets and are associated with cryptographic identities (DID) of the publishers, stored on the blockchain. Knowledge Assets are structured as graph-linked data, have cryptographic fingerprints (Merkle roots) on the blockchain, are timestamped, and are replicated across peers. This ensures that each graph vertex or edge can be verifiably linked to its publisher DID and dataset, enabling data source and integrity verification. See a more detailed information on the DKG technology in [17, 18], on the description of Edge Nodes, that facilitate diverse decentralized AI application within the DKG [16] and on the Core Nodes that ensure reliable access to the DKG in [15]. Blockchain technology is integrated into Decentralized Knowledge Graph to enhance data provenance and immutability, ensuring each piece of knowledge can be verified in terms of source. Smart contracts regulate data access and updates, ensuring trust and security among stakeholders. Blockchains are trust networks established to enable reliable computation through decentralized consensus, operating as a global, dependable computer.

Transparent Sustainability Metrics The presented DKG system with BIM integration used for data exchange, is well suited for life cycle analysis (LCA), and the tranparency of its resulted metrics. At its core, the system extracts a detailed bill of quantities (BoQ) from a building's BIM model and links this data with life cycle inventory (LCI) databases. This facilitates an automated assessment of the environmental impacts associated with the building's construction phase. The integration of DKG technology ensures secure data exchange, verifiability through blockchain-based validation, and seamless scalability—both in terms of data volume and process expansion.

Beyond the construction phase, the framework supports dynamic LCA by incorporating embedded sensor data throughout a building's operational life. This includes real-

https://doi.org/10.52202/080513-0276

time monitoring of parameters such as temperature, energy consumption, and water usage, enabling a more accurate evaluation of use-stage environmental impacts. Such integration is particularly valuable for refining LCA models and adjusting sustainability strategies based on real-world performance data.

And finally, the in-built BIM-based tool (BEXEL manager) allows for a unified visualization of both input parameters and output results of the LCA analysis, giving us an overview of the whole process. This structured approach facilitates comparative scenario analysis, which might be very important, when assessing and comparing LCA metrics for for different building types. For example, the average embodied greenhouse gas emissions of reinforced concrete buildings are 42.68% higher than that of mass timber construction (MTC), when compared over a number of studies [4, 22]. When looking at just this parameter, timber seems to have favorable environmental impact. However, overall impact can vary widely depending on different scenarios considered: variety of building lifespan and climate where it is used, as well as end of life scenarios and carbon sequestration can have massive implications on cradle to grave analysis. For instance, carbon storage of wood can be considered neutral if the wood is burned or left to decay at building demolition phase [4]. To help us make sense of timber building LCA, we expect a wide variety of such considerations will be needed, including processes that have not yet even occurred, as is the case of MTC demolition. A robust, flexible and scalable framework of verified networked data, as the one that was described in the BUILDCHAIN project LCA workgroup, can be incredibly useful.

Integrating as-built measurement data A critical advantage of the BUILDCHAIN DKG framework is its ability to incorporate real-world measurement data from as-built structures, enabling continuous model refinement and supporting digital twinning. By integrating sensor readings, non-destructive testing results, and structural health monitoring (SHM) data, the system bridges the gap between design-phase assumptions and real-world performance, improving predictive accuracy and model validation. This ensures that digital twins evolve dynamically, reflecting actual building behavior rather than relying solely on pre-construction simulations.

The DKG's decentralized architecture plays a key role in managing and verifying as-built data. Sensor readings (e.g., acceleration, temperature, humidity, and strain) are linked to specific building components through semantic relationships, ensuring structured, interoperable, and traceable data storage. Smart contracts regulate access and updates, maintaining data integrity while enabling probabilistic model updating, as will be detailed in the next section. By integrating multi-building datasets, this approach enhances transparency and enables cross-structure comparisons, leading to improved design procedures and more resilient, data-driven decision-making.

2.2 DIGITAL TWINNING

Digital twinning enables a dynamic representation of a building by continuously refining its structural model based on real-world data. This process ensures that as-built performance aligns with as-designed expectations, enhancing both reliability and predictive accuracy. Suppose, a structural model – typically a finite element (FE) model – simulates some measureable property of the building, denoted as $y \in \Re^L$, which represents key aspects of building behavior such as maximum deformations, displacements, or modal properties.

Identifying uncertain modeling parameters Uncertainties in material properties, geometric characteristics, and connection parameters introduce deviations between predicted and actual performance. To account for these modeling uncertainties, we define a set of parameters collected in a vector P in the form of random variables, whose prior distribution $\pi_P(p)$ is determined based on engineering judgment or available measurements. The simulation model then serves as a forward model, predicting the measurable behavior y from a given set of input parameters p, abstractly desribed by the forward operator $\mathcal{M}$:

$$y = \mathcal{M}(p). \tag{1}$$

Bayesian updating with measured data When real-world measurements y_{meas} become available, Bayesian inference allows the refinement of model parameters by updating the prior distribution. Using Bayes' theorem, the updated posterior distribution is given by

$$\pi_{P|y_{\text{meas}}}(p) = \frac{\overbrace{\pi_{y_{\text{meas}}|P}(p)}^{\text{likelihood}}\overbrace{\pi_P(p)}^{\text{prior}}}{\underbrace{\int_{I_P} \pi_{y_{\text{meas}}|P}(p)\pi_P(p)\mathrm{d}p}_{\text{evidence}}}. \tag{2}$$

In this formulation, the likelihood function $\pi_{y_{\text{meas}}|P}(p)$ quantifies the probability of observing the measured building properties y_{meas} given specific values of the parameters p. The term I_P represents the domain over which the parameters P are defined. The likelihood for a specific parameter value p can be written as

$$\pi_{y_{\text{meas}}|P}(p) = \pi_{E_y}(y_{\text{meas}} - \mathcal{M}(p)), \tag{3}$$

where $\pi_{E_y}(\epsilon_y)$ represents the probability distribution of the error model, consisting of the measurement error and the modeling error and ϵ_y denotes a realization of this random error E_y. This formulation implies that the actual measurement y_{meas} can be expressed in an additive form as a sum of the predicted building behavior y_t, computed from the true value of the modeling parameter p_{true} and an unknown realization of the error model

$$y_{\text{meas}} = \underbrace{\mathcal{M}(p_{\text{true}})}_{y_t} + \underbrace{\epsilon_y}_{\text{error}}. \tag{4}$$

In practical examples, the modeling error is often ignored, and measurement error is assumed to be a white noise, with variances originating from expert knowledge of the measurement device that was used, or from the computation the measured values were determined. Even when the distribution π_{E_y} is accurately determined, unfortunately, the likelihood function is often not available in a closed form.

https://doi.org/10.52202/080513-0276

To approximate the posterior distribution, sampling techniques such as the Markov Chain Monte Carlo (MCMC) method, specifically using a random walk strategy, can be employed. This approach involves generating samples in the parameter space, where each step requires evaluating the likelihood—necessitating multiple solutions of the deterministic model —as well as computing the prior. When the deterministic solver is computationally demanding, this procedure can become highly resource-intensive. However, this computational burden can be significantly alleviated by employing surrogate models, which provide efficient approximations of the deterministic solver while preserving accuracy (see e.g. in [20, 21]). For an extensive overview of this Bayesian inversion procedure the reader is directed to the detailed chapter of Friedman et al. [6].

2.3 MULTI-BUILDING TWINING

Identifying joint parameter vector When unconventional materials or connections are used in multiple buildings, measurements from each structure can be integrated for joint parameter updating. Instead of updating parameters separately for each building, a unified approach introduces a joint parameter set Θ mapped to individual building parameters via transformation functions. Shared parameters ensure consistency across models, while independent parameters remain unconstrained. Without the loss of generality, let's suppose we have two similar building structures. One with uncertain parameters P and the other one with parameters Q. By defining maps

$$p = \mathcal{G}(\theta) \quad q = \mathcal{H}(\theta) \tag{5}$$

allows that for the shared parameters the random walk can be done for the two models in a join manner.

Merging measurable building properties and measurements The measurable quantities $y \in \Re^L$ of the first building and the one of the second building $z \in \Re^M$ from both buildings form a joint vector,

$$x = [y, z]^T = [\mathcal{M}(\mathcal{G}(\theta), \mathcal{N}(\mathcal{H}(\theta)]^T, \tag{6}$$

where $\mathcal{M}$ and $\mathcal{N}$ are the two forward operators, mapping from the parameters p and q to the measurable properties of the two buildings y and z. The likelihood computation requires the description of a measurement noise. We assume that the measurement errors of the two buildings are independent, thus their joint distribution is the product of individual error distributions.

Joint updating With this joint formulation, the updating process can be performed in a unified manner, ensuring that shared parameters lead to a consistent posterior distribution. The Bayesian posterior of the joined parameter set is then expressed as

$$\pi_{\Theta|x_{\text{meas}}}(\theta) = \frac{\pi_{x_{\text{meas}}|\Theta}(\theta)\pi_{\Theta}(\theta)}{\int_{I_\Theta} \pi_{x_{\text{meas}}|\Theta}(\theta)\pi_{\Theta}(\theta)\mathrm{d}\theta}. \tag{7}$$

The measured values, y_{meas} and z_{meas} are also merged together into a single vector x_{meas}

Figure 3: Two CLD building analysed: a)Yoker building b)Palisaden building

Using MCMC sampling, the posterior estimates of θ are obtained and mapped back to each model via transformation functions $\mathcal{H}$ and $\mathcal{G}$, improving parameter estimation across buildings.

3 – CASE STUDY: JOINT UPDATING OF DESIGN PARAMETERS OF TALL TIMBER BUILDINGS

We demonstrate the proposed approach using two tall CLT buildings. Traditional Bayesian inference has been effective in identifying design parameters from individual building measurements[11–13]. However, independent updates require manual interpretation to generalize trends. Our approach streamlines this by integrating measurements from multiple buildings into a unified update. Here we will showcase this for the updating properties of the elastic moduli of CLT panels using measured modal properties of two building.

3.1 DATA DISCOVERABILITY VIA BUILDCHAIN

Data structure, ontology The ontology for digital twins of building structures, as depicted in Figure 1, provides a conceptual framework that captures the essential components and relationships involved in the modeling, monitoring, and analysis of buildings. At the center is the building itself, which connects to several interrelated elements. These include the *physical components* of the structure, such as its main load-bearing elements and the sensors attached to it; the various *analysis models* used in the digital twinning process, including simulation models like Finite Element (FE) models, surrogate models that may serve as simplified representations of parametrized FE models, and hybrid models or digital twins that integrate physics-based simulations with observed data by Bayesian model updating. The ontology also encompasses all types of *data* involved in the twinning procedure—ranging from material properties and sensor data collected during forced or ambient vibration tests (e.g., acceleration time series) to processed data such as mode shapes and natural frequencies. Associated with these are the *data processing techniques* used to extract meaningful information, such as operational modal analysis. Furthermore, the ontology includes *performance metrics* such as structural reliability and serviceability, along with the parameters that influence or describe them. Lastly, it incorporates the *methods applied* throughout the digital twinning workflow, from parameter estimation to model updating and uncertainty quantification.

Together, these domains form a structured ontology that facilitates the integration of heterogeneous data sources and analytical approaches. A more detailed view of the knowledge assets involved in the digital twinning process is presented in the mind map in Fig. 6, which illustrates both the knowledge assets used for multi-building updating and those generated during the process, along with their interconnections. Some of these assets are stored directly within the BUILDCHAIN DBL system, while others may be externally maintained and only linked to the DBL. This structured representation not only enables the creation of accurate and robust digital twins but also promotes interoperability, standardization, and cross-building analyses—ultimately contributing to the broader adoption and increased reliability of digital twin technology in the built environment.

Discoverability via BUILDCHAIN Using the BUILDCHAIN user interface, knowledge assets structured in a knowledge graph—according to the ontology described above—can be easily registered. Once a building has been designed, its corresponding administrative information, the physical model (BIM), the designed material properties, and optionally the Finite Element (FE) model can be stored as knowledge assets in the BUILDCHAIN DBL system. Following a measurement campaign, or if the building is equipped with an IoT system, experimental analysts can store measured modal properties as knowledge assets. Through the BEXEL add-on—BUILDCHAIN's integrated BIM application—the IFC model can be enriched with sensor locations and measured modal data by importing these assets using a standard universal file format such as UNV. In this way, measurement data becomes directly visible and accessible within the BIM environment, enhancing transparency and traceability of experimental results (see Fig. 4.)

When designers, researchers, or standardization bodies wish to evaluate the accuracy of standardized design procedures by comparing designed and measured modal properties, this information becomes readily discoverable through OriginTrail's AI-assisted search and data-mining interface. Thanks to the structured representation of data, buildings sharing specific characteristics—such as exceeding a certain height, using a specific design code or being constructed from CLT panels—can be easily identified. It is also possible to filter for buildings with available measurement data. Once the two case study buildings analyzed in this paper are located, users can leverage the BUILDCHAIN application developed for digital twinning and multi-building updating to assess whether design parameters should be revised.

Building 1: Yoker CLT Structure (Glasgow, UK) The first case study focuses on a seven-storey Cross-Laminated Timber (CLT) structure in Glasgow, known as Yoker (Fig. 3) [10], incorporating uncertain design parameters

$$p = [e_1, e_2, e_3, g_1, g_2, q], \tag{8}$$

where e_1, e_2, e_3 represent the elastic moduli of CLT panels along the three primary directions, g_1, g_2 denote in-plane shear moduli and q represents the distributed mass. Uniform priors were assigned based on engineering judgment. To validated the FE model, a forced vibration test was conducted, measuring natural frequencies $f_i^{(I)}$ and mode shapes ψ_i [1]. The measurable outputs were structured as follows:

$$y = \left[f_1^{(I)}, f_2^{(I)}, f_3^{(I)}, f_4^{(I)}, f_5^{(I)}, \psi_1^T, \psi_2^T, \psi_3^T, \psi_4^T, \psi_5^T\right]^T. \tag{9}$$

Gaussian measurement error was assumed, with variances derived from operational modal analysis [12].

Building 2: Palisaden CLT Structure (Ås, Norway) The second case study examines an eight-story CLT structure located in Ås, known as the Palisaden building (Fig. 3). Unlike Yoker, this structure features exposed CLT and plasterboard-covered walls. The uncertain parameters were defined as

$$q = [\gamma_{e1}, \gamma_{G_{12}}, \gamma_{G_{12},\mathrm{ext}}, k_{\mathrm{spring}}, \gamma_\rho], \tag{10}$$

where γ_{e1} scales the vertical elastic modulus of the CLT walls, $\gamma_{G_{12}}$ represents the in-plane shear stiffness scaling factor of the walls, and $\gamma_{G_{12},\mathrm{ext}}$ accounts for external wall stiffness adjustments due to facade effects. k_{spring} models foundation stiffness, while γ_ρ scales the total mass. Non-informative priors were assigned for the modeling parameters, with bounds defined by engineering expertise.

For model calibration, ambient vibration measurements were available, consisting of frequencies for four key vibration modes:

$$z = [f_1^{(II)}, f_2^{(II)}, f_3^{(II)}, f_4^{(II)}]^T. \tag{11}$$

A detailed description of the FE model setup and prior assumptions can be foung in [9, 11].

3.2 JOINT, MULTI-BUILDING TWINNING

Joint parameter description Despite differences in their parameterization, both buildings share a common uncertain parameter representing the same physical property, the vertical elastic modulus of CLT walls. In the Yoker model, this is directly represented as the modulus e_1, while in the Palisaden model, it is scaled relative to the manufacturer's ETA value via:

$$e_1 = \gamma_{e_1} \cdot E_1 \tag{12}$$

To enhance predictive accuracy, a joint parameter update was conducted, introducing a generalized correction for CLT elasticity while simultaneously refining all the other building-specific parameters. This involved defining a joint parameter set θ, composed of ten dimensionless reference parameters (germs)—one shared germ linking both models' elastic modulus and nine independent building-specific germs. Each germ followed a standard uniform distribution $\theta_i \sim \mathcal{U}(0,1)$. The linear maps $\mathcal{G}$ and $\mathcal{H}$ were defined such way, that they scale and shift these reference joint parameters θ the bounds given for the building-specific model parameters.

https://doi.org/10.52202/080513-0276

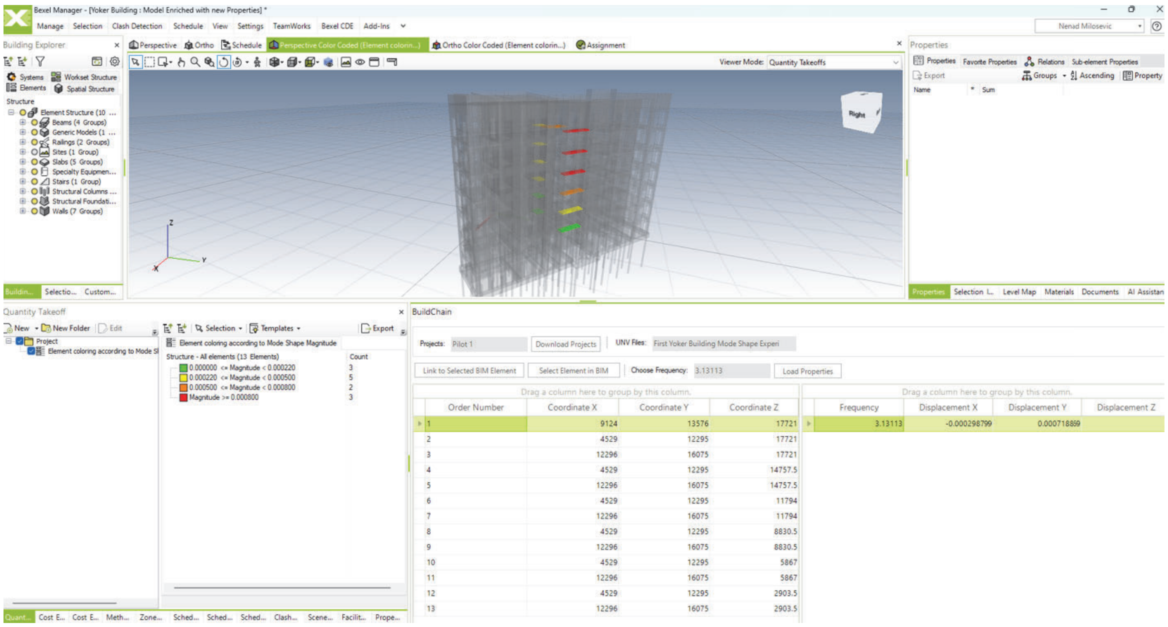

Figure 4: Modal properties visualized in BUILDCHAIN's BIM software, the BEXEL-add-on: the colored elements are the ones to which sensor is attached and the color shows the mode shape values corresponding to the selected mode with frequency 3.13 Hz. The table below also shows the normalized mode shape values in the relevant directions and the coordinates of the sensor.

Joint measurement description The combined measurable output from both structures was formulated as:

$$x = \Big[\underbrace{f_1^{(I)}, \ldots, f_5^{(I)}, \psi_1^T, \ldots, \psi_5^T}_{y}, \underbrace{f_1^{(II)}, \ldots, f_4^{(II)}}_{z}\Big]^T. \quad (13)$$

This enabled a joint update of model parameters, integrating both forced vibration test results (Yoker) and ambient vibration measurements (Palisaden) into a unified Bayesian inference framework.

Joint updating and results The resulting posterior distributions for the jointly updated parameters are shown in Fig. 7. Despite structural and methodological differences, the joint update significantly narrowed the uncertainty in the elastic modulus of CLT walls.

When each model was updated independently, both suggested a downward correction from the manufacturer's ETA value. However, the joint update provided a more robust and generalizable correction, reinforcing confidence in the inferred parameter shift.

Notably, if additional buildings were integrated into the analysis and exhibited similar trends, this would provide strong statistical evidence that ETA values for vertical elastic modulus should be systematically reduced in design standards. Such insights demonstrate how multi-building digital twinning via BUILDCHAIN can drive data-driven improvements in structural design and material specifications.

4 – SUMMARY

This study demonstrates the effectiveness of a joint Bayesian updating framework for refining modeling parameters across multiple Cross-Laminated Timber (CLT) buildings. By integrating structural health monitoring (SHM) data from different structures into a unified probabilistic model, the approach ensures consistency in shared parameters while maintaining building-specific variations. Compared to traditional independent model updates, this joint updating strategy enhances robustness, generalizability, and predictive accuracy, offering valuable insights for both structural design and material optimization.

A key requirement for successful multi-building Bayesian updating is access to reliable and standardized measurement data across different structures. This challenge is effectively addressed by decentralized data-sharing frameworks, such as the BUILDCHAIN project's Decentralized Knowledge Graph (DKG) and Distributed Bayesian Learning (DBL) system. The DKG DBL system plays a crucial role in:

- Ensuring interoperability: By structuring data through semantic ontologies, the DKG facilitates seamless integration of heterogeneous datasets, including FE models, experimental data, and prior distributions.
- Enhancing data accessibility: The decentralized nature of BUILDCHAIN allows for secure, transparent, and permissioned access to high-quality measurement data, overcoming data silos.
- Supporting scalable Bayesian updating: By enabling distributed inference, the DBL system allows users to update model parameters in real-time as new data becomes available, paving the way for continuous learning-based digital twinning.
- Improving model calibration: By aggregating multi-building data, the system facilitates statistically robust parameter updates, reducing reliance on limited single-building datasets and enhancing the reliability of predictive models.

https://doi.org/10.52202/080513-0276

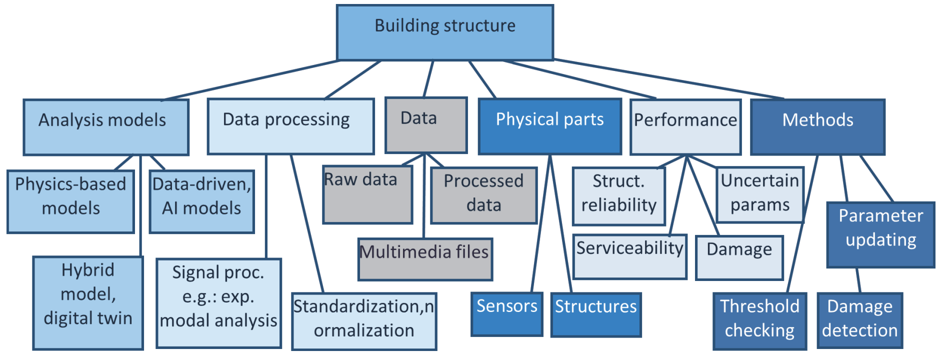

Figure 5: Main elements linked to digital twinning procedure

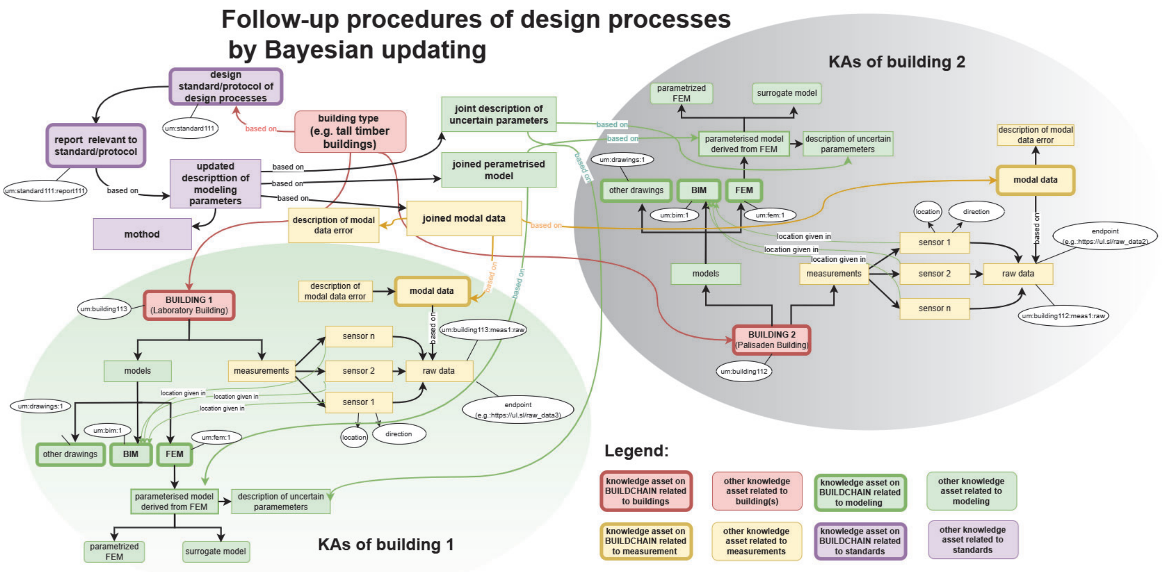

Figure 6: Mind map of design parameter updating: different type of BUILDCHAIN knowledge assets for multi-building design update, and their connection

The integration of digital twinning with decentralized data frameworks marks a transformative step in structural engineering and SHM. By embedding probabilistic inference capabilities into knowledge graphs, BUILDCHAIN not only supports individual building monitoring but also enables large-scale, multi-building intelligence. This capability is particularly relevant for next-generation smart infrastructure, where real-time model updates based on live sensor data can significantly improve resilience, safety, and sustainability. This study lays the groundwork for a scalable, data-driven approach to digital twinning, ensuring more accurate, efficient, and resilient engineering practices in the future.

5 – ACKNOWLEDGMENT

This work is funded by the BUILDCHAIN project. BUILDCHAIN has received funding from the European Union's Horizon Europe research and innovation program under grant agreement 101092052. Support of the European Union project RRF-2.3.121-2022-00004 within the framework of the Artificial Intelligence National Laboratory Program is also acknowledged.

REFERENCES

[1] W. K. Ao, A. Pavic, B. Kurent, and F. Perez. "Novel FRF-based fast modal testing of multi-storey CLT building in operation using wirelessly synchronised data loggers." In: *Journal of Sound and Vibration* 548.July 2022 (2023), p. 117551. ISSN: 0022-460X. DOI: `10.1016/j.jsv.2023.117551`. URL: `https://doi.org/10.1016/j.jsv.2023.117551`.

[2] M. G. Bevilacqua, G. Caroti, P. Croce, N. Friedman, F. Landi, and A. Piemonte. "The Horizon Europe BUILDCHAIN Project Presentation: Trustworthy Building Life-Cycle Knowledge Graph for Sustainability and Energy Efficiency." In: *SCIRES-IT: Scientific Research and Information Technology* 13.2 (2023), pp. 137–150. URL: `http://www.sciresit.it/article/view/13796`.

https://doi.org/10.52202/080513-0276

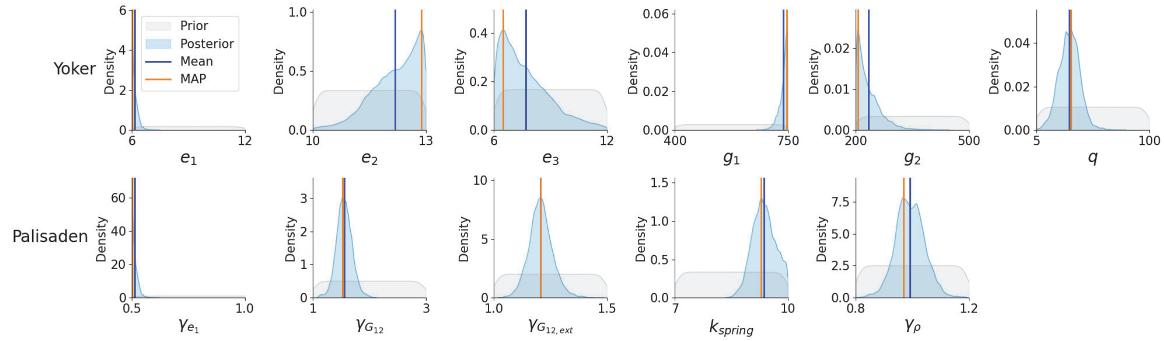

Figure 7: Result of joint updating: the prior (grey), posterior (blue) distributions of the parameters, the mean posterior and the maximum a-posteriori (MAP) estimate. The upper row corresponds to the parameters of the Yoker building, the lower the parameters of the Palisaden building. The first parameters of the two models are updated from a common germ resulting in the same compensation of elastic moduli.

[3] DBL Study Team: Ecorys, TNO, Arcadis and Contecht. *Technical guidelines for digital building logbooks Guidelines to the Member States on setting up and operationalising digital building logbooks under a common EU framework*. Tech. rep. 2023. URL: `https://www.ecorys.com/app/uploads/2019/02/DBL-Technical-Guidelines-for-DBLs.pdf`.

[4] Z. Duan, Q. Huang, and Q. Zhang. "Life cycle assessment of mass timber construction: A review." In: *Building and Environment* 221 (2022), p. 109320. ISSN: 0360-1323. DOI: `https://doi.org/10.1016/j.buildenv.2022.109320`. URL: `https://www.sciencedirect.com/science/article/pii/S0360132322005534`.

[5] N. Friedman et al. *Design of the BUILDCHAIN system*. Ed. by N. Friedman. Accessed: 2025-03-06. 2025. URL: `%5Curl%7Bhttps://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e511b236d1&appId=PPGMS%7D`.

[6] N. Friedman, C. Zoccarato, E. Zander, and H. G. Matthies. "A Worked-out Example of Surrogate-based Bayesian Parameter and Field Identification Methods." In: 2021, pp. 61–76. ISBN: 9781315232973. DOI: `10.1201/b22018-10`. URL: `https://www.taylorfrancis.com/chapters/edit/10.1201/b22018-10/worked-example-surrogate-based-bayesian-parameter-field-identification-methods-no%C3%A9mi-friedman-claudia-zoccarato-elmar-zander-hermann-matthies?context=ubx`.

[7] M. Gómez-Gil, A. Espinosa-Fernández, and B. López-Mesa. "A new functionality for the digital building logbook: Assessing the progress of decarbonisation of national building sectors." In: *Environmental Impact Assessment Review* 105 (2024), p. 107393. DOI: `https://doi.org/10.1016/j.eiar.2023.107393`.

[8] M. Gómez-Gil, A. Espinosa-Fernández, and B. López-Mesa. "Contribution of New Digital Technologies to the Digital Building Logbook." In: *Buildings* 12.12 (2022). DOI: `10.3390/buildings12122129`.

[9] B. Kurent. "Probabilistic Modelling and Model Updating of Tall Timber Buildings." PhD thesis. Slovenia: University of Ljubljana, 2023.

[10] B. Kurent, B. Brank, and W. K. Ao. "Model updating of seven-storey cross-laminated timber building designed on frequency-response-functions-based modal testing." In: *Structure and Infrastructure Engineering* 19.2 (2023), pp. 178–196. ISSN: 17448980. DOI: `10.1080/15732479.2021.1931893`. URL: `https://doi.org/10.1080/15732479.2021.1931893`.

[11] B. Kurent, N. Friedman, A. Aloisio, D. Pasca, R. Tomasi, and B. Brank. "Bayesian model updating of eight-storey CLT building using modal data." In: *Probabilistic Engineering Mechanics* 77 (2024), p. 103642. ISSN: 0266-8920. DOI: `https://doi.org/10.1016/j.probengmech.2024.103642`. URL: `https://www.sciencedirect.com/science/article/pii/S026689202400064X`.

[12] B. Kurent, N. Friedman, W. K. Ao, and B. Brank. "Bayesian updating of tall timber building model using modal data." In: *Engineering Structures* 266 (2022), p. 114570. ISSN: 18737323. DOI: `10.1016/j.engstruct.2022.114570`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S0141029622006745`.

[13] B. Kurent, N. Friedman, and B. Brank. "Modelling of Multi-Storey Cross-Laminated Timber Buildings for Vibration Serviceability." In: *Buildings* 14.3 (2024). ISSN: 2075-5309. DOI: `10.3390/buildings14030689`. URL: `https://www.mdpi.com/2075-5309/14/3/689`.

[14] M. Malinovec Puček, A. Khoja, E. Bazzan, and P. Gyuris. "A Data Structure for Digital Building Logbooks: Achieving Energy Efficiency, Sustainability, and Smartness in Buildings across the EU." In: *Buildings* 13.4 (2023). DOI: `10.3390/`

buildings13041082. URL: https://www.mdpi.com/2075-5309/13/4/1082.

[15] OriginTrail. *DKG Core Node*. 2025. URL: https://docs.origintrail.io/build-with-dkg/dkg-core-node (visited on 03/28/2025).

[16] OriginTrail. *DKG Edge Node*. 2025. URL: https://docs.origintrail.io/build-with-dkg/dkg-edge-node (visited on 03/28/2025).

[17] OriginTrail. *DKG Key Concepts*. 2025. URL: https://docs.origintrail.io/key-concepts/dkg-key-concepts#knowledge-assets (visited on 03/28/2025).

[18] OriginTrail. *OriginTrail Website*. 2025. URL: https://docs.origintrail.io/ (visited on 03/28/2025).

[19] M. Signorini, M. C. Dejaco, and S. Lupica Spagnolo. "The Evolution of Digital Building Logbook: Exploring Building Information Gathering Systems to Boost Building Maintenance and Renovation." In: *Applied Sciences* 15.2 (2025). DOI: 10.3390/app15020771.

[20] M. Sodan, A. Urbanics, N. Friedman, A. Stanic, and M. Nikolić. "Comparison of Machine Learning and gPC-based proxy solutions for an efficient Bayesian identification of fracture parameters." In: *Computer Methods in Applied Mechanics and Engineering* (2025). URL: https://api.semanticscholar.org/CorpusID:275024757.

[21] D. Xiu. "Fast numerical methods for stochastic computations: A review." In: *Communications in Computational Physics* 5 (2009), pp. 242–272. URL: https://api.semanticscholar.org/CorpusID:11872147.

[22] A. Younis and A. Dodoo. "Cross-laminated timber for building construction: A life-cycle-assessment overview." In: *Journal of Building Engineering* 52 (2022), p. 104482. ISSN: 2352-7102. DOI: https://doi.org/10.1016/j.jobe.2022.104482. URL: https://www.sciencedirect.com/science/article/pii/S2352710222004958.

 https://doi.org/10.52202/080513-0276