



Leveraging Structural Health Monitoring Data Through Avatars to Extend the Service Life of Mass Timber Buildings

Mariapaola Riggio^{1*}, Michael Mrissa^{2,3}, Miklós Krész^{2,4,5}, Jan Včelák^{2,6}, Jakub Sandak^{2,4} and Anna Sandak^{2,3}

¹Oregon State University, Corvallis, OR, United States, ²InnoRenew CoE, Izola, Slovenia, ³Faculty of Mathematics, Natural Sciences and Information Technologies, University of Primorska, Koper, Slovenia, ⁴Andrej Marušič Institute, University of Primorska, Koper, Slovenia, ⁵Department of Applied Informatics, University of Szeged, Szeged, Hungary, ⁶Czech Technical University in Prague, University Centre for Energy Efficient Building, Buštěhrad, Czechia

OPEN ACCESS

Edited by:

Meisam Gordan,
University College Dublin, Ireland

Reviewed by:

Hossein Mohammadhosseini,
Universiti Teknologi Malaysia, Malaysia

*Correspondence:

Mariapaola Riggio
mariapaola.riggio@oregonstate.edu

Specialty section:

This article was submitted to
Structural Sensing, Control and Asset
Management,
a section of the journal
Frontiers in Built Environment

Received: 01 March 2022

Accepted: 16 May 2022

Published: 08 June 2022

Citation:

Riggio M, Mrissa M, Krész M, Včelák J,
Sandak J and Sandak A (2022)
Leveraging Structural Health
Monitoring Data Through Avatars to
Extend the Service Life of Mass
Timber Buildings.
Front. Built Environ. 8:887593.
doi: 10.3389/fbuil.2022.887593

Mass timber construction systems, incorporating engineered wood products as structural elements, are gaining acceptance as a sustainable alternative to multi-story concrete or steel-frame structures. The relative novelty of these systems brings uncertainties on whether these buildings perform long-term as expected. Consequently, several structural health monitoring (SHM) projects have recently emerged to document their behavior. A wide and systematic use of this data by the mass timber industry is currently hindered by limitations of SHM programs. These limitations include scalability, difficulty of data integration, diverse strategies for data collection, scarcity of relevant data, complexity of data analysis, and limited usability of predictive tools. This perspective paper envisions the use of avatars as a Web-based layer on top of sensing devices to support SHM data and protocol interoperability, analysis, and reasoning capability and to improve life cycle management of mass timber buildings. The proposed approach supports robustness, high level and large-scale interoperability and data processing by leveraging the Web protocol stack, overcoming many limitations of conventional centralized SHM systems. The design of avatars is applied in an exemplary scenario of hygrothermal data reconstruction, and use of this data to compare different mold growth prediction models. The proposed approach demonstrates the ability of avatars to efficiently filter and enrich data from heterogeneous sensors, thus overcoming problems due to data gaps or insufficient spatial distribution of sensors. In addition, the designed avatars can provide prediction or reasoning capability about the building, thus acting as a digital twin solution to support building lifecycle management.

Keywords: mass timber buildings, hygrothermal monitoring, avatars, microclimate data, mold risk models

1 INTRODUCTION

This perspective paper briefly introduces current advances and existing challenges of SHM to support service life management of timber buildings and to control conditions conducive to biodegradation (**Section 1**). In **section 2**, a novel approach is presented, based on decentralized systems (i.e., avatars) for data analysis and performance prediction. The approach is exemplified in

an application to 1) reconstruct moisture content and microclimate data, and 2) iteratively fit data into existing mold risk models.

1.1 Problem Statement

The timber construction industry has changed over the recent years due to engineering developments and evolution of wood-based materials. Mass timber construction has elevated the prospects of utilizing wood in the form of engineered wood products as the primary structural material in mid- and high-rise structures. Because this approach to building is relatively novel, there are still some uncertainties on whether these structures perform long-term as expected. One critical area of concern is the intersection of durability and hygrothermal performance (i.e., response to heat, air and moisture transfer phenomena) of such systems. Specifically, exposure to moisture through in-service leaks or ambient high humidity poses a potential risk of triggering biotic attack by mold or fungi. Moisture control is particularly crucial in mass timber buildings. Mass timber elements, differently than light-frame construction, have the capacity to store large volumes of water and exhibit much slower wetting and drying behavior through their thickness (Schmidt et al., 2019). To address these concerns, hygrothermal monitoring has been gaining popularity to document and control the behavior of mass timber buildings during their service life. Several SHM projects have been successfully implemented (Riggio and Dilmaghani, 2020; Baas et al., 2021), also with the scope of developing reliable predictive models of the long-term performance of these materials. While there is a huge potential in the broad adoption of SHM and data exchange, a wide and systematic use of available data collected in mass timber buildings is currently hindered by certain limitations of SHM programs, such as 1) scalability; 2) difficulty of data integration within and between projects; 3) scarcity of relevant data (spatial resolution and data gaps); 4) low efficiency for data post-processing; 5) limited usability of predictive tools.

The objective of this perspective paper is to propose a methodological framework that relies on the concept of avatars, decentralized computing agents based on Web languages and protocols, to overcome interoperability issues and integrate data from a diversity of sensors within and between buildings.

1.2 Emerging Approaches to SHM and Their Relevance for Service Life Management of Timber Structures

Data mining (DM) is a rapidly emerging approach also in the field of SHM. A review by (Gordan et al., 2022) found that most DM applications are in structural dynamics for damage detection and system identification. Artificial Neural Network (ANN) techniques were found to be the most suitable DM technique in these applications, because of their high flexibility, scalability and learning capability. To account for uncertainty of deterioration processes in timber structures, statistical methods are often used. Srikanth and Arockiasamy (2020) applied deterministic, stochastic and ANN-based deterioration models

using National Bridge Inventory data to predict remaining useful life of timber bridges. Visual inspection data were used for Markov models by (Ranjith et al., 2013) to predict deterioration of timber bridges. Tran et al. (2020) used a dynamic Bayesian Network framework with a simplified deterioration model by (Wang et al., 2008), to spatially model decay occurrence in timber members and assess members' reliability. Other authors have used non-destructive techniques to model biodegradation in timber (e.g., Sousa et al., 2013; Sandak et al., 2015a) reviewed DM for characterization and prediction of biodegradation in timber structures; the authors reported use of DM to analyze infrared spectra for clustering and classification tasks (e.g., assess the type of degrading agents and mechanisms) and to build prediction models (e.g., in Zanetti et al., 2005; Sandak A et al., 2015; Sandak et al., 2015b).

DM for SHM has been mainly exploited using conventional computing systems, where data is stored and processed in a centralized way (i.e., a cloud database), leading to limitations such as single point of failure, low fault tolerance, high latency, network bandwidth consumption and big data problems. These limitations are increasingly impactful when there is a need to perform SHM data mining tasks across different projects managed by different organizations and in various geographical locations.

Existing strategies to address these problems rely on large-scale replication and attempt to locate cloud servers as close as possible to the data origin. However, these solutions are costly and create problems for data integration, synchronization, and exchange between cloud servers. Dang et al. (2022) proposed a solution using a layer of fog computing prior to the cloud layer to reduce the computational demand of DM tasks in SHM. Alternative solutions can be osmotic (Villari et al., 2016) and/or edge computing (Garcia Lopez et al., 2015). In that case, the data are partially (osmotic) or fully (edge) processed and managed directly on the sensor. Only the relevant information, instead of the original raw data, is uploaded to the cloud after pre-processing. More computationally demanding tasks are performed afterwards on the cloud server, in the case of osmotic computing.

A few decentralized frameworks have been proposed to support SHM in different ways (Sim and Spencer, 2009; Hackmann et al., 2012; Liu et al., 2013; Swartz, 2013; Jiang et al., 2021). (Swartz, 2013) highlighted the relevance of decentralized computing approaches to SHM to facilitate data integration, improve its usage, and reduce communication costs. However, the vision of decentralized computing is limited to resource-constrained devices, specific protocol stacks, and bound to drivers/devices, operating systems, programming languages, or frameworks. Jiang et al. (2021) proposed deep auto-encoder and manifold learning as a decentralized unsupervised framework to identify, locate, and quantify structural damage using unprocessed vibration data. However, the decentralized approach concerns the different sensors that capture the data, and not the software that supports storage and processing, which instead follows a typical centralized approach. Hackmann et al. (2012) proposed a decentralized approach for damage localization by computing data directly onto the sensors. Their

work demonstrated above 60% gain in latency and energy consumption when compared to a centralized approach. In (Liu et al., 2013) a modal analysis algorithm through overlapping data subsets is distributed to all sensors for computation and reconstitution of the global mode shape. While existing work shows the interest of decentralized computing to analyze sensor data, it does not address the interoperability problems that occur when a variety of sensors are used in different places. This perspective paper addresses this problem proposing a Web-based approach.

Sim and Spencer (2009) reviewed different approaches for decentralized data aggregation. The report shows how to apply well-known strategies to a concrete use case and provides concrete development and configuration aspects to implement different algorithms over resource-constrained devices. Despite the success of such implementations, the bigger vision of an interoperable ecosystem is still missing. Savaglio and Fortino (2021) presented an edge-computing methodology for Internet-of-Thing (IoT) data mining, enabling descriptive and predictive tasks. While promising, the approach has not been tested in a real-case scenario nor applied having a specific industry in mind. Also in this case, the opportunity for high level and large-scale interoperability and data processing, which the Web protocol stack is designed to support, is not addressed.

1.3 State-Of-The-Art Approach to Wood Hygrothermal Monitoring and Service Life Management

Wood moisture content (MC), relative humidity (RH) and air temperature (T) data can be used to analyze and predict different phenomena affecting the durability and serviceability of timber structures. Resistance-type moisture meters are commonly used to monitor MC in timber structures (Dietsch et al., 2015). One of the advantages of this technique is the possibility to measure MC in different plies/depths of a mass timber panel, thus allowing to capture moisture gradients. On the other hand, high variability of hygrothermal conditions in a timber structure limits representation of complex MC distributions through resistance readings (Riggio et al., 2019; Schmidt and Riggio, 2019). Some critical events or areas of concern may not be captured when spatial distribution of sensors is insufficient. RH and T data in the proximity of the area of concern may be used to predict wood MC variations (Autengruber et al., 2020). Assuming normal use conditions, the wood will respond to the ambient following so-called sorption isotherms, which indicate variations of equilibrium moisture content values between 0 and 100% RH at varying temperatures and for a given species (Glass and Zelinka, 2021). While these correlations are not perfect and not always applicable, they can be used for missing data reconstruction.

Long data series can support predictive analysis. Several approaches for modeling service life of timber structures are summarized by (van Niekerk et al., 2021). Most of those approaches rely on dose-response models, which confront the time-wise integrated deterioration dose with the intrinsic material resistance (Hukka and Viitanen, 1999; Thelandersson and Isaksson, 2013). The “critical dose” is reached when the exposure of the material equals or exceeds its resistance. The

exposure dose is determined according to the historical variation of MC and T, identifying all time periods promoting the growth of microorganisms. The exposure dose can be computed using data from sensors monitoring intensity, duration, and frequency of pertinent climate events.

Most available dose-response models have been developed and validated only for some selected wood species (Thelandersson et al., 2011). Considering that the mass timber industry expands geographically and explores local resources (Ahmed and Arocho, 2020), there is a need to calibrate prediction models for more species and different mass timber products (Anderson et al., 2021). This high variability suggests the need of an iterative, systematic, and incremental approach to improve detection and prediction tools and make them applicable to different scenarios, building types and mass timber products.

2 AVATAR-ASSISTED HYGROTHERMAL MONITORING AND ASSESSMENT OF TIMBER STRUCTURES

2.1 Multi-Level Decentralized Networks for SHM

This section provides a definition of the avatar concept, and a description of the communication framework to support SHM data integration and enhance data analysis and data mining tasks. Avatars are software entities that provide a virtual abstraction to extend sensors on the Web and support the digital representation of buildings and their elements (Mrissa et al., 2015). They support proactive behavior and prediction of building conditions thanks to reasoning or machine learning mechanisms, better interoperability through data enrichment with semantic annotations and the use of Web languages and protocols, such as REST architectural style (Fielding, 2000), HTTP protocol (Fielding, 2014), and JSON/XML data format (Bray, 2014). Thus, they provide a digital twin implementation (Mi et al., 2021), in a way similar to the servant defined by the W3C (Kovatsch et al., 2020).

Avatars are designed to build communities in which everyone autonomously contributes to the common objectives. Each avatar embeds the set of necessary algorithms to drive its behavior to proactively act on a detected situation.

The avatar community as a decentralized system forms a multilayer data processing and computation model. Multiple levels of sensor and IoT systems are organized as a multilayer network (Kivelä et al., 2014), where the network of a particular building and the network of different buildings are distinct. Both data processing and computational solutions of this architecture need different approaches for optimization of the network design and routing protocols.

To reduce the complexity of design and operation (Arcaute et al., 2021), these networks are organized in two levels: Sensor nodes and gateways. Each sensor is arranged to a gateway node through a path determined by the routing. All the collected data are shared among the gateway nodes. Gateway nodes in this way have, on one hand, a central role in one single routing layer, and, on the other hand, serve as connection among the layers. A promising approach can be to design the layers with an optimal distributed gateway placement. On this level, data processing and

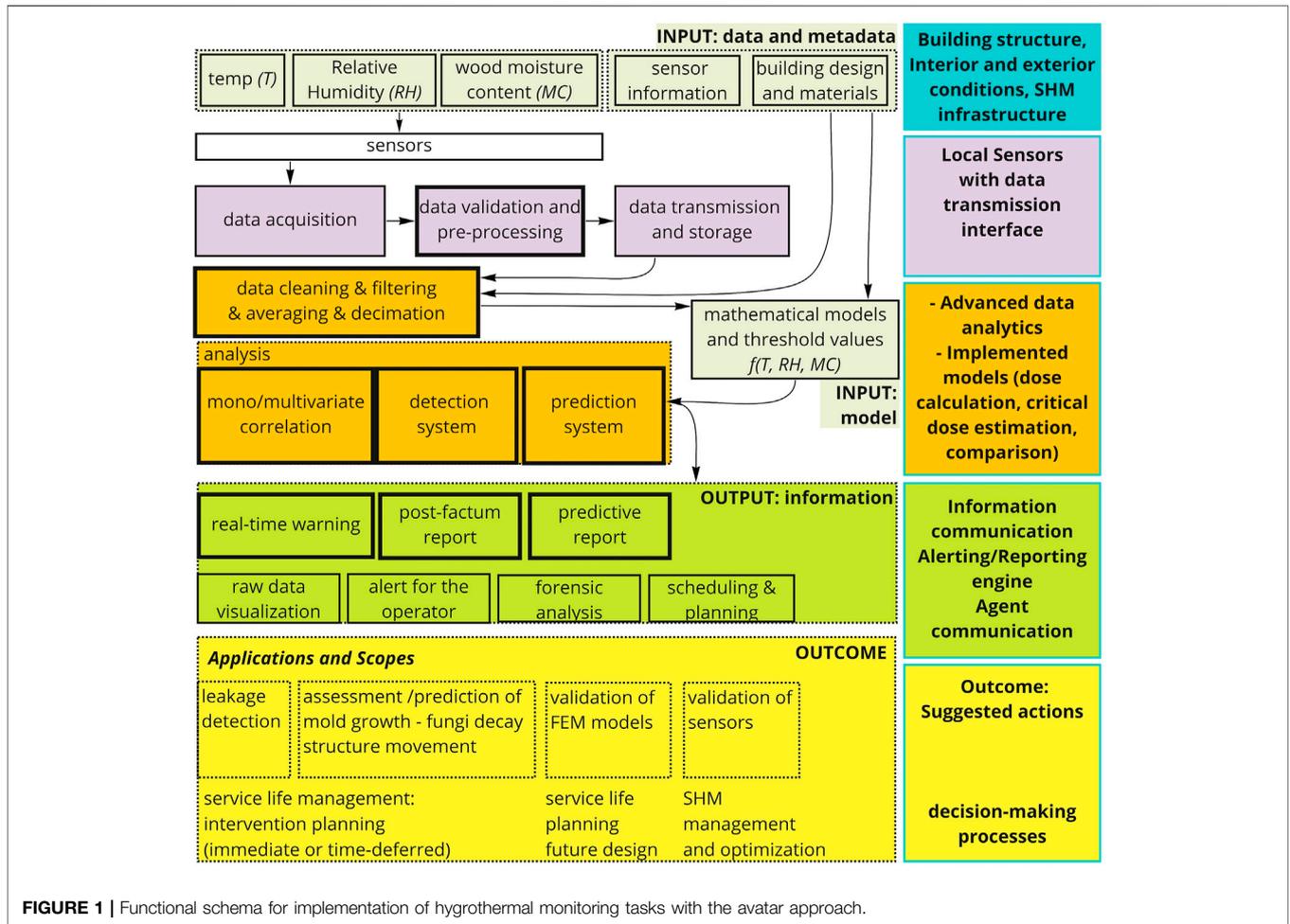


FIGURE 1 | Functional schema for implementation of hygrothermal monitoring tasks with the avatar approach.

data fusion are executed toward the gateways with the assumption of a fixed family of protocols. The aggregated computation in a fully connected system of gateways can be organized in a second phase using the same family of protocols.

The so-called gossip protocols (Jelasy, 2011) are proposed here as a reliable solution for decentralized computation of aggregated values. They replicate the rumor spreading in social networks. In addition to their data processing efficiency (Robin et al., 2021), they have high computational power in aggregated mathematical calculations (Kempe et al., 2003). Recent studies proved that gossip-based machine learning is competitive with federated learning (Hegedűs et al., 2021).

2.2 Peer-To-Peer Knowledge Base for Service Life Management of Mass Timber Buildings: Exemplary Applications and Preliminary Results

Figure 1 illustrates SHM tasks, systems, inputs, and outputs along with resulting actions, exemplified for the case of hygrothermal monitoring of wooden structures. The use of avatars as an additional layer on top of sensing devices allows to create a “common software ground”, bypassing hardware differences and inconsistencies.

In this approach, an avatar locally computes the relevant information about the physical object, i.e., it preprocesses the sensor data using associated contextual information about both the monitoring system (the sensors) and the monitored system (the building, the materials). In this phase, avatars can provide a suitable platform for advanced data analytics in a sensor network, as they allow sensors to dynamically make the best decision depending on the available information. Dynamic improvement of the up-to-date algorithms used for data analytics can take place by communicating and comparing local results with other avatars. It is particularly useful in the case of building monitoring, as, for instance, increased humidity, leaks, and condensation detected by a single sensor may be confronted with readings of other surrounding sensors in the close vicinity. In this case, an avatar issues a request to neighbor avatars to check if their data mismatches, correlates or extends their own. The next avatar can in turn further forward relevant data to others. Triggering proactive data sharing activates other actions within the network, such as filling data gaps using the data from neighbor avatars or validating measurements considering additional sensor readings.

An example of information sharing between functionally heterogeneous sensors is when heterogeneous sensors are used to

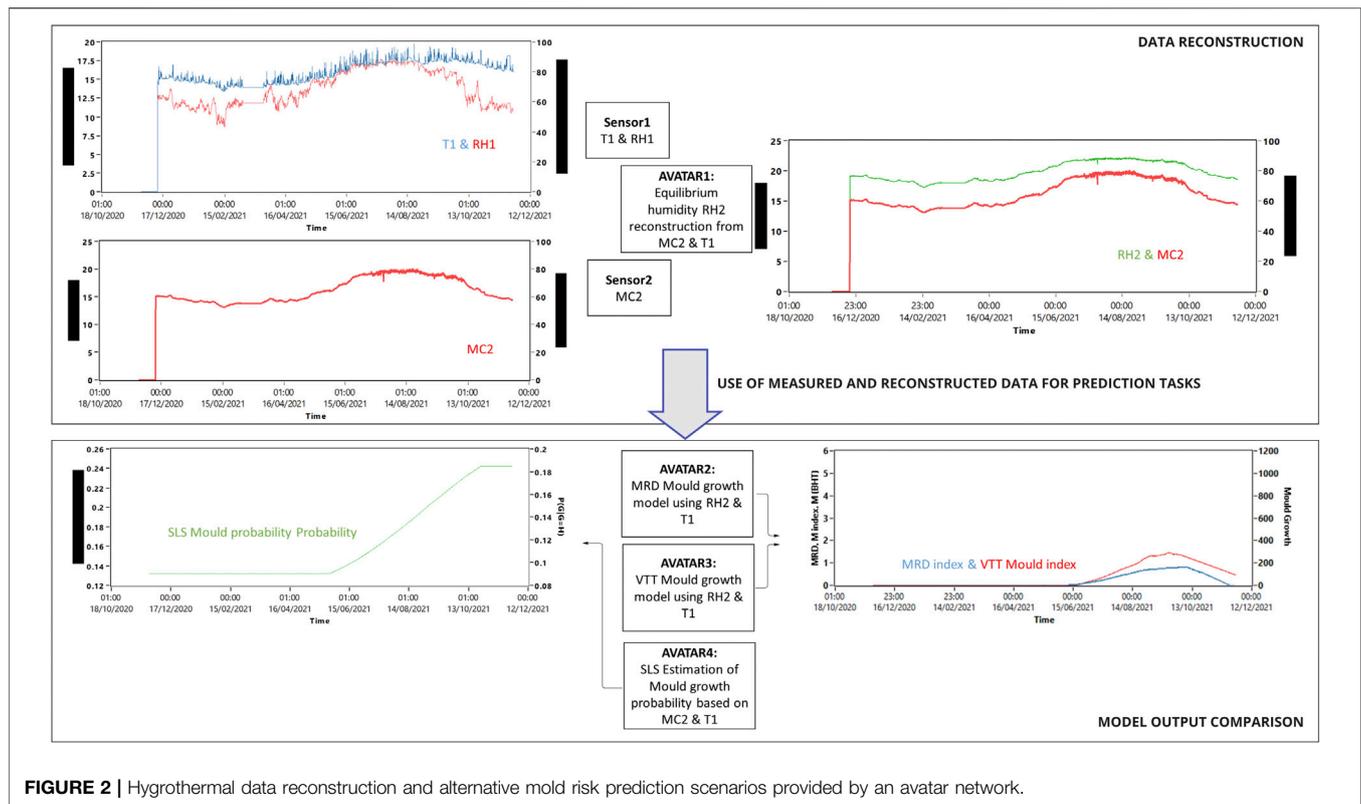


FIGURE 2 | Hygrothermal data reconstruction and alternative mold risk prediction scenarios provided by an avatar network.

fill data gaps, deriving one missing parameter from other correlated ones. The decentralized computation is supported by a dynamic routing to the gateway nodes. This process is exemplified in **Figure 2**, which shows hygrothermal monitoring data from a mass timber building. “Avatar 1” was used to reconstruct RH values in one location 2 where only MC data was available, using sorption-isotherms (assuming similar T in both locations). The approach of data recovery in this example is different from regression tasks performed, especially in the field of static monitoring, to correlate measurements of same types of sensors (see for instance a Bayesian dynamic regression model developed by Zhang et al., 2022, and a deep learning-based recovery method for temperature data proposed by Liu et al., 2020). However, the proposed framework does not exclude the use of alternative methods to rebuild missing data.

Prediction tasks can benefit from avatars by integrating monitoring data over time into one or many mathematical models. Preliminary findings show the effectiveness of avatars in using different hygrothermal parameters to apply alternative mold growth prediction models. As shown in **Figure 2**, reconstructed RH data were used by Avatars 2 and 3 to apply models developed by (Hukka and Viitanen, 1999; Viitanen et al., 2000; and Thelandersson et al., 2011). At the same time, “Avatar 4” used MC values from location 2 for mold risk prediction according to the serviceability limit state (SLS) model (Lepage et al., 2022). The SLS model is the only method applicable, if exclusively MC data are available. While all the three avatars predicted onset of mold, the one using the SLS model did not predict decrease of risk when suboptimal conditions for mold growth were present (**Figure 2**). Given the dynamic nature of hygrothermal conditions in timber buildings, the possibility to

compare predictions from different datasets and models is key, to evaluate risk scenarios for mold growth and make informed decisions.

Avatar can calculate models for prediction initially from single location data, enriched with contextual information. Information on architectural details and materials can be integrated to define the “critical dose” or structure “resistance”. The safety status of the structure or risk of its unconformity is then determined by confronting the resistance with the exposure dose. Based on their individually calculated risk indexes, avatars can collaborate to realize complex tasks at the building level or among multiple buildings such as data correlation as described above, or continuous improvement of detection sensitivity to reduce the number of false alerts and undetected problems. Similar circumstances, in the same building or in different buildings, can be compared by avatars in a synergistic approach to enhance predictability of certain risks.

Decision-making processes, such as predictive maintenance (PdM), can be supported by avatars as well. This is concretely implemented through mathematical modeling, such as linear regression techniques applied on the data coming from the sensors, combined with thresholds, that will predict critical conditions, and a set of rules that provide knowledge about appropriate mitigation measures (Bouabdallaoui et al., 2021). Use of a decentralized approach for PdM is beneficial as it addresses some of the PdM challenges highlighted by (Compare et al., 2019), such as the need to update and adjust PdM model using the knowledge and data incrementally available throughout the service life of a building, or even, from different buildings.

3 CONCLUDING REMARKS

In this paper, we present a vision based on avatars to support SHM. Avatars rely on Web languages and protocols to overcome integration problems that arise when gathering data from multiple sensors, within and between buildings. They also provide data analysis and reasoning capacity through semantic enrichment. They enable data exploitation as they form an abstraction layer on top of the sensor network.

One of the most critical aspects and bigger benefits of an avatar-based approach to SHM is the possibility to generate a ripple effect in the interested community, in this case the mass timber industry. This ripple effect amplifies with each new building and new monitoring data added in the network, as well as with the duration of a monitoring project. In our vision, the “big data” generated from SHM projects is an advantage, and not a problem, as each avatar is a knowledge base that contributes to refining other avatars’ knowledge base and to devising common models that become more and more accurate as their number grows.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

REFERENCES

- Ahmed, S., and Arocho, I. (2020). Mass Timber Building Material in the U.S. Construction Industry: Determining the Existing Awareness Level, Construction-Related Challenges, and Recommendations to Increase its Current Acceptance Level. *Clean. Eng. Technol.* 1, 100007. doi:10.1016/j.clet.2020.100007
- Anderson, R., Dawson, E., Muszyński, L., Beck, B., Hammond, H., Kaiser, B., et al. (2021). *2021 International Mass Timber Report*. Missoula, Montana: FBN. 2021. ISBN: 978-1-7337546-4-4.
- Arcaute, E., Barthelemy, M., Batty, M., Caldarelli, G., Gershenson, G., Helbing, D., et al. (2021). Future Cities: Why Digital Twins Need to Take Complexity Science on Board. unpublished manuscript. Available at: https://www.researchgate.net/publication/354446988_Future_Cities_Why_Digital_Twins_Need_to_Take_Complexity_Science_on_Board (Accessed February 1, 2022).
- Autengruber, M., Lukacevic, M., and Füssl, J. (2020). Finite-element-based Moisture Transport Model for Wood Including Free Water above the Fiber Saturation Point. *Int. J. Heat Mass Transf.* 161, 120228. doi:10.1016/j.ijheatmasstransfer.2020.120228
- Baas, E. J., Riggio, M., and Barbosa, A. R. (2021). A Methodological Approach for Structural Health Monitoring of Mass-Timber Buildings under Construction. *Constr. Build. Mater.* 268, 121153. doi:10.1016/j.conbuildmat.2020.121153
- Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L., and Bennadji, B. (2021). Predictive Maintenance in Building Facilities: A Machine Learning-Based Approach. *Sensors* 21 (4), 1044. doi:10.3390/s21041044
- Bray, T. (2014). The Javascript Object Notation (Json) Data Interchange Format. *RFC* 7158, 1–16.
- Compare, M., Baraldi, P., and Zio, E. (2019). Challenges to IoT-Enabled Predictive Maintenance for Industry 4.0. *IEEE Internet Things J.* 7 (5), 4585–4597. doi:10.1109/IIOT.2019.2957029
- Dang, H. V., Tatipamula, M., and Nguyen, H. X. (2021). Cloud-Based Digital Twinning for Structural Health Monitoring Using Deep Learning. *IEEE Transac. Indus. Inform.*

AUTHOR CONTRIBUTIONS

MR and MM contributed to conception of this perspective paper. MR, JV, AS, and JS contributed to define the application context and requirements. MM and MK defined the proposed technological solutions. All authors contributed to manuscript draft and revision. All authors read and approved the submitted version.

FUNDING

ForestValue has received funding from the European Union’s Horizon 2020 research and innovation program. The authors gratefully acknowledge the European Commission for funding the InnoRenew project (Grant Agreement \#739574) under the Horizon2020 Widespread-Teaming program and the Republic of Slovenia (Investment funding of the Republic of Slovenia and the European Regional Development Fund). They also acknowledge the Slovenian Research Agency ARRS for funding the project J2-2504, BI-US/22-24-153, BI-US-20-054 and CLICK DESIGN, “Delivering fingertip knowledge to enable service life performance specification of wood”, (No. 773324) supported under the umbrella of ERA-NET Cofund ForestValue by the Ministry of Education, Science and Sport of the Republic of Slovenia.

- Dietsch, P., Franke, S., Franke, B., Gamper, A., and Winter, S. (2015). Methods to Determine Wood Moisture Content and Their Applicability in Monitoring Concepts. *J. Civ. Struct. Health Monit.* 5 (2), 115–127. doi:10.1007/s13349-014-0082-7
- R. Fielding and J. Reschke (Editors) (2014). *RFC 7230: Hypertext Transfer Protocol (HTTP/1.1): Message Syntax and Routing*. Internet Engineering Task Force (IETF). Available at: <http://www.rfc-editor.org/info/rfc7230>. doi:10.17487/RFC7230
- Fielding, R. T. (2000). Architectural Styles and the Design of Network-Based Software architectures. PhD Dissertation. Irvine: University of California.
- Garcia Lopez, P., Montresor, A., Epema, D., Datta, A., Higashino, T., Iamnitchi, A., et al. (2015). Edge-centric Computing: Vision and Challenges. *SIGCOMM Comput. Commun. Rev.* 45 (5), 37–42. doi:10.1145/2831347.2831354
- Glass, S., and Zelinka, S. (2021). *Moisture Relations and Physical Properties of Wood*. Madison, WI: Forest Products Laboratory, 4–1. Chapter 4 in *FPL-GTR-282*.
- Gordan, M., Sabbagh-Yazdi, S.-R., Ismail, Z., Ghaedi, K., Carroll, P., McCrum, D., et al. (2022). State-of-the-art Review on Advancements of Data Mining in Structural Health Monitoring. *Measurement* 193, 110939. doi:10.1016/j.measurement.2022.110939
- Hackmann, G., Sun, F., Castaneda, N., Lu, C., and Dyke, S. (2012). A Holistic Approach to Decentralized Structural Damage Localization Using Wireless Sensor Networks. *Comput. Commun.* 36 (1), 29–41. doi:10.1016/j.comcom.2012.01.010
- Hegedüs, I., Danner, G., and Jelasity, M. (2021). Decentralized Learning Works: An Empirical Comparison of Gossip Learning and Federated Learning. *J. Parallel Distributed Comput.* 148, 109–124. doi:10.1016/j.jpdc.2020.10.006
- Hukka, A., and Viitanen, H. A. (1999). A Mathematical Model of Mould Growth on Wooden Material. *Wood Sci. Technol.* 33 (6), 475–485. doi:10.1007/s002260050131
- Jelasity, M. (2011). “Gossip,” in *Self-Organising Software*. Editors G. Di Marzo Serugendo, M. P. Gleizes, and A. Karageorgos (Berlin Heidelberg: Springer), 139–162. doi:10.1007/978-3-642-17348-6_7

- Jiang, K., Han, Q., Du, X., and Ni, P. (2021). A Decentralized Unsupervised Structural Condition Diagnosis Approach Using Deep Auto-encoders. *Computer-Aided Civ. Infrastructure Eng.* 36 (6), 711–732. doi:10.1111/mice.12641
- Kempe, D., Dobra, A., and Gehrke, J. (2003). “October. Gossip-Based Computation of Aggregate Information,” in 44th Annual IEEE Symposium on Foundations of Computer Science, 2003 (Cambridge, MA: IEEE), 482–491.
- Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., and Porter, M. A. (2014). Multilayer Networks. *J. complex Netw.* 2 (3), 203–271. doi:10.1093/comnet/cnu016
- Kovatsch, M., Matsukura, R., Lagally, M., Kawaguchi, T., Toumura, K., and Kajimoto, K. (2020). Web of Things (WoT) Architecture. W3C Recommendation. World Wide Web Consortium (W3C), W3C Recommendation. Available at: <https://www.w3.org/TR/wot-architecture/>.
- Lepage, R., Glass, S. V., Bastide, P. d. l., and Mukhopadhyaya, P. (2022). Serviceability Limit State Model for Fungal Growth on Wood Materials in the Built Environment. *J. Build. Eng.* 50, 104085. doi:10.1016/j.job.2022.104085
- Liu, H., Ding, Y. L., Zhao, H. W., Wang, M. Y., and Geng, F. F. (2020). Deep Learning-Based Recovery Method for Missing Structural Temperature Data Using LSTM Network. *Struct. Monit. Maintenance* 7 (2), 109–124. doi:10.12989/smm.2020.7.2.109
- Liu, X., Tang, S., and Xiaohua, X. (2012). “Smart Wireless Sensor Nodes for Structural Health Monitoring,” in *Intelligent Sensor Networks The Integration of Sensor Networks, Signal Processing and Machine Learning*. Editor B. Hu and Q. Hao Edn. 1. Boca Raton, 77–91.
- Mi, S., Feng, Y., Zheng, H., Wang, Y., Gao, Y., and Tan, J. (2021). Prediction Maintenance Integrated Decision-Making Approach Supported by Digital Twin-Driven Cooperative Awareness and Interconnection Framework. *J. Manuf. Syst.* 58, 329–345. doi:10.1016/j.jmsy.2020.08.001
- Mrissa, M., Médini, L., Jamont, J.-P., Le Sommer, N., and Laplace, J. (2015). An Avatar Architecture for the Web of Things. *IEEE Internet Comput.* 19 (2), 30–38. doi:10.1109/mic.2015.19
- Ranjith, S., Setunge, S., Gravina, R., and Venkatesan, S. (2013). Deterioration Prediction of Timber Bridge Elements Using the Markov Chain. *J. Perform. Constr. Facil.* 27 (3), 319–325. doi:10.1061/(asce)cf.1943-5509.0000311
- Riggio, M., and Dilmaghani, M. (2020). Structural Health Monitoring of Timber Buildings: A Literature Survey. *Build. Res. Inf.* 48 (8), 817–837. doi:10.1080/09613218.2019.1681253
- Riggio, M., Schmidt, E., and Mustapha, G. (2019). Moisture Monitoring Data of Mass Timber Elements during Prolonged Construction Exposure: The Case of the Forest Science Complex (Peavy Hall) at Oregon State University. *Front. Built Environ.* 5, 98. doi:10.3389/fbuil.2019.00098
- Robin, F., Sericola, B., Anceume, E., and Mocquard, Y. (2021). Stochastic Analysis of Rumor Spreading with Multiple Pull Operations. *Methodol. Comput. Appl. Probab.*, 1–17. doi:10.1007/s11009-021-09911-4
- Sandak, A., Sandak, J., and Riggio, M. (2015). Estimation of Physical and Mechanical Properties of Timber Members in Service by Means of Infrared Spectroscopy. *Constr. Build. Mater.* 101, 1197–1205. doi:10.1016/j.conbuildmat.2015.06.063
- Sandak, J., Sandak, A., and Riggio, M. (2015b). Characterization and Monitoring of Surface Weathering on Exposed Timber Structures with a Multi-Sensor Approach. *Int. J. Archit. Herit.* 9 (6), 674–688. doi:10.1080/15583058.2015.1041190
- Sandak, J., Sandak, A., and Riggio, M. (2015a). Multivariate Analysis of Multi-Sensor Data for Assessment of Timber Structures: Principles and Applications. *Constr. Build. Mater.* 101, 1172–1180. doi:10.1016/j.conbuildmat.2015.06.062
- Savaglio, C., and Fortino, G. (2021). A Simulation-Driven Methodology for IoT Data Mining Based on Edge Computing. *ACM Trans. Internet Technol.* 21 (2), 1–22. doi:10.1145/3402444
- Schmidt, E. L., Riggio, M., Barbosa, A. R., and Mugabo, I. (2019). Environmental Response of a CLT Floor Panel: Lessons for Moisture Management and Monitoring of Mass Timber Buildings. *Build. Environ.* 148, 609–622. doi:10.1016/j.buildenv.2018.11.038
- Schmidt, E., and Riggio, M. (2019). Monitoring Moisture Performance of Cross-Laminated Timber Building Elements during Construction. *Buildings* 9 (6), 144. doi:10.3390/buildings9060144
- Sim, S. H., and Spencer, B. F., Jr. (2009). Decentralized Strategies for Monitoring Structures Using Wireless Smart Sensor Networks. NSEL Report Series. Report No. NSEL-019. Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign.
- Sousa, H. S., Sørensen, J. D., Kirkegaard, P. H., Branco, J. M., and Lourenço, P. B. (2013). On the Use of NDT Data for Reliability-Based Assessment of Existing Timber Structures. *Eng. Struct.* 56, 298–311. doi:10.1016/j.engstruct.2013.05.014
- Srikanth, I., and Arockiasamy, M. (2020). Deterioration Models for Prediction of Remaining Useful Life of Timber and Concrete Bridges: A Review. *J. Traffic Transp. Eng. Engl. Ed.* 7 (2), 152–173. doi:10.1016/j.jtte.2019.09.005
- Swartz, R. A. (2013). “Decentralized Algorithms for SHM over Wireless and Distributed Smart Sensor Networks,” in *Earthquakes and Health Monitoring of Civil Structures* (Dordrecht: Springer), 109–131. doi:10.1007/978-94-007-5182-8_4
- Thelandersson, S., Isaksson, T., Frühwald, E., Toratti, T., Viitanen, H., Grull, G., et al. (2011). *Service Life of Wood in Outdoor above Ground Applications Engineering Design Guideline*. Lund, Sweden: Lund University, 29.
- Thelandersson, S., and Isaksson, T. (2013). Mould Resistance Design (MRD) Model for Evaluation of Risk for Microbial Growth under Varying Climate Conditions. *Build. Environ.* 65, 18–25. doi:10.1016/j.buildenv.2013.03.016
- Tran, T.-B., Bastidas-Arteaga, E., and Aoues, Y. (2020). A Dynamic Bayesian Network Framework for Spatial Deterioration Modelling and Reliability Updating of Timber Structures Subjected to Decay. *Eng. Struct.* 209, 110301. doi:10.1016/j.engstruct.2020.110301
- van Niekerk, P. B., Brischke, C., and Niklewski, J. (2021). Estimating the Service Life of Timber Structures Concerning Risk and Influence of Fungal Decay-A Review of Existing Theory and Modelling Approaches. *Forests* 12 (5), 588. doi:10.3390/f12050588
- Viitanen, H., Hanhijärvi, A., Hukka, A., and Koskela, K. (2000). “Modelling Mould Growth and Decay Damages,” in *Healthy Buildings 2000*, Espoo, 6–10 August 2000 (FISIAQ).3, 341–346.
- Villari, M., Fazio, M., Dustdar, S., Rana, O., and Ranjan, R. (2016). Osmotic Computing: A New Paradigm for Edge/cloud Integration. *IEEE Cloud Comput.* 3 (6), 76–83. doi:10.1109/mcc.2016.124
- Wang, C.-h., Leicester, R. H., and Nguyen, M. (2008). Probabilistic Procedure for Design of Untreated Timber Poles In-Ground under Attack of Decay Fungi. *Reliab. Eng. Syst. Saf.* 93 (3), 476–481. doi:10.1016/j.res.2006.12.007
- Zanetti, M., Rials, T. G., and Rammer, D. (2005). “NIR-monitoring of In-Service Wood Structures,” in *Metropolis and Beyond: Proceedings of the 2005 Structures Congress and the 2005 Forensic Engineering Symposium*, New York, NY, April 20–24, 2005, 1–9. doi:10.1061/40753(171)40
- Zhang, Y. M., Wang, H., Bai, Y., Mao, J. X., and Xu, Y. C. (2022). Bayesian Dynamic Regression for Reconstructing Missing Data in Structural Health Monitoring. *Struct. Health Monit.* doi:10.1177/14759217211053779

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher’s Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Copyright © 2022 Riggio, Mrissa, Krész, Včelák, Sandak and Sandak. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.