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Risk-Informed Digital Twin (RDT) for the Decarbonization of the Built Environment: The Australian Residential Context †

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Abstract: Urban communities are complex systems. According to the holistic perspective of the systems thinking theory, the "whole is not the sum of its parts, but rather is a product of the parts' interactions". This systems-thinking approach is commonly applied to analyse urban systems and developments. This study introduces the Risk-informed Digital Building Twin (RDBT) based on the Risk-informed Digital Twin (RDT), a novel digitalization technology incorporating an integrated multi-dimensional multi-stakeholders decision-making system under uncertainty. In the RDBT, energy-efficient, resilient, and sustainable systems/subsystems of civil engineering can be considered at the scale of the single building to assess different needs. Monitored data are critical to performing comprehensive near real-time lifecycle holistic analyses through the framework of Sustainable and Resilient Based Engineering. An apartment building located in Sydney, Australia, has been selected for future deployment of the RDBT.

Keywords: risk analysis; energy consumption; sustainability; apartment buildings; residential buildings; continuous monitoring; urban development; holistic approach; OpenAIUQ

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1. Introduction

Globally, buildings are responsible for 39% of all energy and processes related to the total greenhouse gas (GHG) emissions [1]. The reduction of these emissions is challenged by the increasing population growth, urbanization, and demand for new buildings. The latter could double by 2050, so the process of decarbonization of new building stocks is urgent. Although energy efficiency is improving the building performance, this is not enough for the decarbonization of the built environment.

To address the goals of the Paris Agreement, the World Green Building Council sets as a target: (i) by 2030, the 40% reduction of embodied emissions of new buildings, infrastructures, and renovations, (ii) by 2050, the achievement of net-zero embodied emissions of the built environment [2,3]. The suggested strategies cover operational, indirect, and embodied emissions. For example, Amiri et al. [4] suggests that if 80% of buildings are constructed with timber by 2040, the CO_2 emissions in Europe could be cut up to 0.42 Gt.

In [5], it is suggested that the examination of the decarbonization of the whole lifecycle of the built environment needs a holistic approach that is able to: (i) encompass the boundaries of the national economies across a set of time windows, and (ii) include broad environmental and socio-economic factors in order to target the United Nations Sustainable Development Goals (SDGs) by 2030. Taking timber buildings as an example, once again, it was found in [5] that timber used to construct new buildings stores the carbon and if the number of new buildings is greater than the number of demolished ones, this provides a temporary carbon bank. Moreover, total embodied emissions in timber buildings decrease over time, therefore they have lower lifecycle embodied emissions than concrete buildings. From the other side, care should be devoted to (i) relevant end-of-life emissions of timber buildings [6] and (ii) sustainable management of the forests, where low harvest rates have to be kept in order to avoid detrimental climate impacts [7].

These recent findings show how achieving net zero operational and embodied GHG emissions of the built environment requires a multi-disciplinary, multi-level holistic view of urban communities. This task is challenging due to the several sources of uncertainty, including but not limited to the changing urban climate, interdependencies between critical infrastructures, and interactions between multiple stakeholders (e.g., occupants, developers, consultants, builders, practitioners, social institutions, and relevant government agencies) and evaluation of multi-dimensional (e.g., economy, society, health, and infrastructures) societal impacts determined by the occurrence of extreme events (e.g., floods, haze, blast, urban heat island, and heatwaves). Therefore, there is the need to: (i) develop novel models for uncertainty quantification and risk assessment of the impacts of the urban heat challenge, (ii) compare and rank the lifecycle holistic performances of new building typologies and/or design concepts, innovative material, or construction processes, and (iii) understand, predict, and control the interdependencies between different systems for urban governance and policymaking concerning the urban grand challenges.

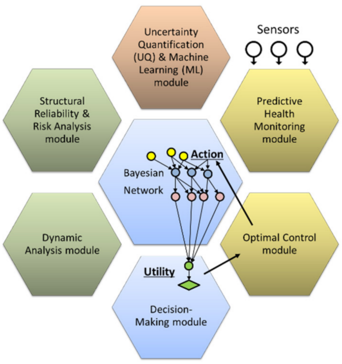
On the other side, we are living now in the fourth (digital) industrial revolution, where Artificial Intelligence (AI) has risen as a highly disruptive technology given the big data technologies and availability, high-performance computing, and the introduction of novel learning algorithms (e.g., Machine Learning and Deep Learning). Much has been claimed about the power of these techniques, however, there is little theoretical foundation that could show how they work on real problems tailored to the built environment. In fact, there is practical evidence that some techniques of Machine Learning are a good fit for a certain category of problems but not for others. Moreover, especially concerning extreme events, there is no clear evidence about the most suitable algorithms to be adopted. To this aim, there is the need of integrating the domain expertise with the state-of-the-art tools of data science, risk analysis and management, stochastic analysis, and multi-criteria decision making under uncertainty. Having this in mind, the following research questions are of main concern: (i) choice of the optimal algorithms of risk-informed machine learning for any category of problems, (ii) validation/verification of the models, including their parameters and model uncertainty, (iii) probabilistic sensitivity analysis of the most important parameters, and (iv) development of suitable risk-informed decision-making systems able to describe behaviour and preferences of different stakeholders.

2. Risk-Informed Digital Twin

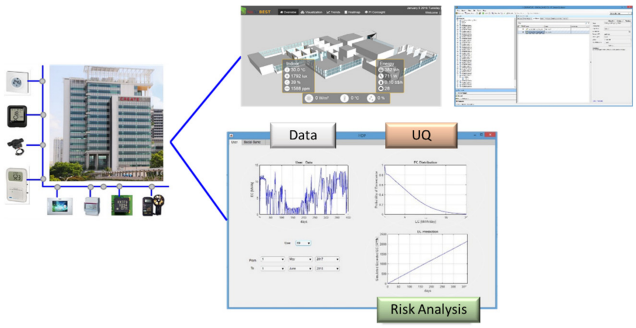
To address the research questions stated above, a very attractive tool is represented by Digital Twin (DT) technologies. Following [8], the DT is defined as a living digital model of real-world buildings, processes, structures, people, and systems created and maintained in order to answer questions about its physical part, the Physical Twin (PT). In the case of the built environment, the PT is represented by the smart buildings and infrastructures. Through networks of sensors and the Internet of Things (IoT) full synchronization, perpetual learning process and updating between the two twins is targeted. Usually, predictions are pursued through data-driven algorithms and tools in the DT. To take into account all the sources of uncertainty during the whole lifecycle, the concept of Risk-informed Digital Twin (RDT) was introduced in [8] which integrates methods and tools of Statistics, Uncertainty Quantification, Risk Analysis with Machine Learning.

The core of the RDT is the framework of Sustainable and Resilient Based Engineering (SRBE), introduced in [8], and thought of as the natural extension of the Performance-Based Engineering approach to Socio-Ecological-Technical (SET) systems under uncertainty. SRBE is formulated using the Bayesian Network (BN) [9] which is a probabilistic model that facilitates the efficient graphical representation of the dependence among random variables. The main features of BN are: (i) their capacity in predicting probabilistic updating when new information is acquired, e.g., through a network of sensors or from observations after inspection, (ii) their transparent modelling, which allows their adoption by users with limited background in probabilistic or reliability analysis, (iii) their ability to model time-dependent uncertain parameters easily [10]. In the RDT, the Dynamic Bayesian Networks are used to model stochastic processes of all the quantities of interest. This allows a transparent lifecycle modelling of the involved space- and time-dependent uncertainties and a clear description of the dynamic spatial evolution of the optimal decision.

The RDT has the following submodules: (i) module of data-driven Uncertainty Quantification (UQ) and Machine Learning (ML), (ii) module of data-driven Structural Reliability and Risk Analysis, (iii) module of data-driven Predictive Health Monitoring, (iv) module of Decision-Making Tool under uncertainty, including social aspects, and (v) module of Optimal Control. A preliminary version of the RDT, with standard tools of Uncertainty Quantification and Machine Learning, has been already deployed in the SinBerBEST office in Singapore. Figure 1 shows that the data of the smart building are monitored in real-time, the module of UQ evaluates the probability distribution of the daily energy consumption, while the module of Risk Analysis predicts annual lifecycle energy consumption. Lifecycle sustainability analyses in terms of near real-time predictions of lifecycle cost, energy expenditure, and operational emissions through the RDT are described in [8].



(a)



(b)

Figure 1. Risk-informed Digital Twin (RDT) [8]: (**a**) OpenAIUQ modules; (**b**) deployment of the RDT to the SinBerBEST office.

The module of data-driven Uncertainty Quantification and Risk Analysis, called AIUQ, is grounded on a novel framework based on the information theory [8,11–13]. AIUQ is capable to describe, inside the same framework, algorithms, methods, and tools typically used by different communities of researchers. This implies that a new generation of algorithms of risk-informed machine learning for the built environment can be generated. The basic tools of UQ are collected in the open-source software OpenAIUQ [14].

In [8,15] lifecycle holistic performances of a realistic building in California are evaluated. They include lifecycle probabilistic performances of cost, structural safety and injuries/fatalities, embodied, and operational emissions. The findings show that due to post-hazard repair and maintenance, buildings need to be resilient in order to be eco-efficient. The adoption of probabilistic metrics (instead of their expected values) is relevant for risk-informed decision making. It is well recognized that decision-makers are typically risk-averse, and they prefer being aware of the confidence level of predictions.

3. Conclusions

This study presents the RDT that incorporates the five levels of DT, including simulation, intelligent and semi-autonomous DT. It is composed of several modules (e.g., Uncertainty Quantification and Machine Learning, Health Monitoring, Risk Analysis, Decision Making under uncertainty, and Optimal Control). Following the conclusions drawn in [8], the following competitive outcomes from the deployment of the RDT are expected. RDT implements the framework of SRBE, formulated in [8]. SRBE is capable of describing the time-dependent dynamic response of the systems under uncertainty. In the absence of information and available data, the consequences may be determined through the existing databases, repositories, and tools. If available, these could be enriched with BIM, using different levels of detail. Although the importance of novel design concepts and technologies and materials for sustainable and resilient design (e.g., timber design [5]) are recognised, currently the design codes and guidelines are not updated in this regard. Probabilistic sensitivity analyses can detect the most relevant parameters affecting holistic performances. The model uncertainties of the adopted solutions can be reduced, together with the introduction of new accurate computational models. Another gap of knowledge is the lack of suitable databases to be shared with stakeholders. RDT may help in developing these databases and in laying the basis for green transition and circular economy.

As a further development, it is planned to deploy the RDT in a smart building located in Australia. The developed open-source software OpenAIUQ inside RDT technologies will be applied to the Australian residential context and validated, using monitored data from a 7-storey apartment building located in Sydney and completed in 2018. Four representative pilot studies will be considered in this investigation: (i) human occupancy prediction and modelling, (ii) energy modelling and calibration, (iii) anthropogenic heat generated by air-conditioning, and lifecycle performances in terms of heat emission, CO_2 emissions, and cost, and (iv) energy saving through human-centric designs, driven by the behaviour and preferences of the occupants. This will be the first example of RDT deployment to a whole instrumented building, in particular with reference to Australia. Technological innovations tailored to Australia can be detected as a result of this application.

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