The Utilization of Building Energy Simulation Results as Input Data for Building Level Digital Shadows and System Level Digital Twins: A Framework for Investigation

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ABSTRACT

The energy performance gap between simulated and measured energy performance of buildings is a well-recognized challenge the construction industry is facing. The causes that contribute to the phenomenon emerge during all stages of a construction project with a vast majority of those causes emerging in the design and operational stages. In the design stage, simplification of energy simulation models and the use of various assumptions lead into huge differences between simulated and measured energy values. On the other hand, lack of continuous monitoring is another major contributor to the phenomenon. A wide range of evidence in literature stress on the need of addressing these issues that fall under a category of technical causes and under a broader category of cross-cutting causes such as lack of accountability. This is achieved by exploring how simulation tools could be considered as potential source of exploring different design ideas in early design stages and how to utilize simulation results in commissioning stage and early operational stages to prevent deviations from simulated energy performance. For the causes associated with the operational stage, the potential of digital twins and digital shadows is explored which have proved their potential to address many challenges the construction industry is facing. However, challenges remain in interpreting and creating digital twins, prompting researchers to explore their potential through the lens of traditional building energy simulation tools. This has resulted in some ambiguity when it comes to distinguishing the unique advantages of digital twins over other digital models. In this paper, a link is made between technical causes that emerge in the design and operational stages with potential means of addressing them to tackle the broader issue associated with lack of accountability. A brief state-of-the-art review is provided to clarify the distinctions between various digital models. The paper then proposes a framework that focused on how simulation tools should be employed to better narrow the energy performance gap, and identifying the data needed to create digital shadows and twins. Given the complexity of buildings and creating digital twins, the authors propose the notion of system-level digital twins and building-level digital shadows to accelerate the adoption of these technologies. This approach is expected to contribute significantly to the mitigation of the energy performance gap.

Keywords: Digital Twins, Digital Shadows, Building Energy Simulation, BIM, Energy Performance Gap.

INTRODUCTION

Research evidence shows that many factors contributing to the Energy Performance Gap (EPG) in buildings arise from the creation of inaccurate energy models (Zou et al., 2018). Several researchers argue that these issues originate during the design stage, stemming from the complexity of making accurate assumptions about system performance, occupant behaviour, or the challenges in predicting climate conditions. Others

attribute the EPG to the epistemological beliefs of energy analysts who develop energy models (Imam et al., 2017). Energy simulation models are recognized as abstractions that simplify complex realities (Gorse et al., 2016). Additionally, the lack of ground truth data makes it difficult to make more accurate predictions during the design stage (Coleman et al., 2018). However, the accuracy of simulation models plays a critical role in both quantifying and mitigating the EPG. This raises two key questions regarding the EPG:

1. How can energy simulation tools be seen as a potential means for mitigating the EPG, rather than being considered a contributing factor?
2. What is the role simulation tools could play in the operational stage of buildings?

In parallel, innovative technological means are emerging to address many of the challenges in the construction industry. It has been suggested that "the success of digitalization in construction is similar to that of the transformation in the information technology sector, where adopting suitable digital methods and techniques plays a vital role in the transformation process" (Bajpai & Misra, 2022). However, the successful adoption of digital methods and techniques depends on a thorough understanding of their definitions, potential, and capabilities. One such technology that has seen rapid uptake in recent years is Digital Twins (DTs). A DT is defined as "a dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.), representing the exact state of its physical twin at any given point in time by exchanging real-time data and maintaining historical data. It is not only the DT that mimics its physical twin; any changes in the DT are mirrored by the physical twin as well" (Singh et al., 2021). In both the manufacturing and industrial sectors, there has been ambiguity regarding the definition of DTs and how they differ from digital models and digital shadows (DS). This issue is also observed in the Architecture, Engineering, and Construction (AEC) industry. For instance, de Wilde (2023) emphasized the importance of clearly delineating the technology to ensure meaningful technological progress. Similarly, Ghorbani and Messner (2024) identified 35 definitions of DTs, from which five are related to the Built Environment (BE). On an urban scale, the complexity increases further, reviewing various literature proves that there is not a unified approach for describing the different layers of DTs (Alva et al., 2022; Ferré-Bigorra et al., 2022; Jiang et al., 2022; Lu et al., 2020; Lv et al., 2022). The potential of DTs will remain difficult to realize unless their definition and capabilities are better understood.

This paper makes a link between technical causes that contribute to the energy performance gap that emerge in the design and operational stages with potential means of addressing them to tackle a broader issue associated with lack of accountability. The aim of the paper is achieved by exploring ways to simplify and accelerate the adoption of DTs and DSs for buildings by leveraging data from energy simulation models created during the design stage. A secondary goal of this research is to illustrate how simulation tools could be regarded as a means of achieving intended energy targets. To achieve these aims, the following objectives are set:

1. Differentiate between various digital.
2. Propose a framework for investigation and implementation.
3. Explore the limitations of current research, barriers to implementation, and avenues for future research.

METHOD

Various methods are employed to achieve the aims of this research. To address the first two objectives, a brief state-of-the-art review is conducted, exploring the interface between DTs and the EPG. Also, the literature distinguishes between traditional simulation models, Building Information Modeling (BIM), DS, and DTs to provide a solid foundation for developing the framework. A framework is then developed focused on the design and operational stages. The part focused on the design stage focus on the quantitative data that should be obtained from simulation tools and how this data should be utilized during the operational stage to create a building-level DS and system-level DTs. The part focused on the operational-stage will outline how data is exchanged between system-level DTs, building-level DS and simulation tools.

DIGITAL TWINS AND THE ENERGY PERFORMANCE GAP

The concept of DTs is emerging in the construction industry, although different interpretations of this notion coexist. Some research publications explore the role of DTs in reducing the EPG, although they do not always explicitly refer to the EPG. Francisco et al. (2020) explicitly examined the role of DTs in reducing the EPG through real-time data monitoring. They argued that analysing real-time data allows for the development of sophisticated energy management techniques that account for inefficient occupant behaviours and management practices. Mengual Torres et al. (2022) created a DT to monitor the performance of energy-intensive devices, such as air conditioners and lighting systems. Their study aimed to inform facility managers about devices that could be replaced with more energy-efficient alternatives.

Ni et al. (2021) leveraged artificial intelligence (AI), cloud computing, and the Internet of Things (IoT) to create DTs for historical buildings, to optimize their energy efficiency. By analyzing both historical and real-time data, they were able to improve the energy efficiency of these buildings. Real-time data was continuously transferred from the physical building to the DT, enabling the prediction of future energy consumption and maintenance needs using AI models. Tan et al. (2022) developed a DT for lighting systems based on a dynamic BIM model and computer vision. Similarly, Zakharov et al. (2019) developed a DT that proposed a method for collecting comprehensive data from a network of sensors to automate heat supply. Real-time monitoring allowed them to propose tailored solutions for heat management, and the algorithms they developed enabled the classification of different rooms based on their temperature characteristics.

DISTINCTION BETWEEN DIFFERENT MODELS

Chong et al. (2021) defines building energy simulation models as physics-based models that calculate a building's energy performance and the thermal comfort of its occupants, influenced by various inputs such as building geometry, operating hours, HVAC systems, and internal loads. According to de Wilde (2014), a growing concern regarding these models is the discrepancy between predicted and measured energy performance. Mantesi et al. (2018) found that modeling gaps, often caused using default settings and assumptions, can result in deviations of up to 26% in simulation outcomes. BIM, on the other hand, represent the continuous and consistent use of digital information across the design, construction, and operation stages (André Borrmann et al., 2018). Sepasgozar (2021) notes that some researchers refer to BIM and DTs as similar concepts, often using them interchangeably.

A DS on the other hand is a virtual model that represents a physical entity with one-way data flow (Errandonea et al., 2020). This data transfer typically occurs from the physical entity to the digital model (Peldon et al., 2024). A DS reflects the state of physical objects, but changes occur only in the digital representation (Bergs et al., 2021). In contrast, DTs, as stated by Zhang et al. (2020), emphasize bi-directional and automated two-way data flow. Furthermore, Fuller et al. (2020) stress that not every digital representation of a physical object or entity qualifies as a DT. A true DT must model the logic and rules governing the processes or behaviors of its physical counterpart (Chen et al., 2020). Additionally, it should encode data and offer a comprehensive view of the entity's past and present states, as well as future predictions, whether for assets or processes (Sepasgozar, 2021). Ghorbani and Messner (2024) categorized DTs based on the relationships between them and their physical counterparts and the level of connectivity, as shown in table one below.

Table 1: Relationships between Digital and Physical Twins (Ghorbani & Messner, 2024)

Relationship	***Connectivity***
One to one	*a single DT directly corresponds to a physical twin*
One to many	*a DT linked to multiple physical twins*
Many to one	*Multiple DTs converging on a single physical twin*
Many to many	*Multiple DTs connected to multiple physical twin*

Table two outlines six key features of 3D models, BIM, DTs and DSs such as representation, data flow, update mechanism, synchronization, control, and integration.

Table 2: Features of 3D models, BIM, DTs, DSs adapted from (Austin et al., 2020; Hämäläinen, 2020; Peldon et al., 2024; Quek et al., 2023; Sepasgozar, 2021; Shahat et al., 2021).

3D Models	
Representation	*Static*
Data flow	*None*
Update Mechanism	*No update over time*
Synchronization	*No synchronization*
Control	*None*
Integration	*Visual representation*
BIM	
Representation	*Static digital representation with physical information for management*
Data flow	*Manual interaction with physical data*
Update Mechanism	*Require manual data entry*
Synchronization	*Static, manual synchronization*
Control	*None or limited to the design phase*
Integration	*Design and construction information*
Digital Shadows	
Representation	*Dynamic*
Data flow	*Physical to virtual*
Update Mechanism	*Physical to digital update*
Synchronization	*Real-time synchronisation*
Control	*No control of PS*
Integration	*Partial with updates from physical systems (PS)*
Digital Twins	
Representation	*Dynamic*
Data flow	*Continuous and Bi-directional data flow*
Update Mechanism	*Automatic in both directions*
Synchronization	*Real-time synchronisation*
Control	*Information control from digital to PS*
Integration	*Full data management and exchange between virtual and PS*

FRAMEWORK

The current interoperability challenges between the various tools used by different stakeholders in the AEC industry are significant (Pierpaolo Ruttico, 2024). These tools are typically used by different stakeholders involved in a construction project, with minimal participation from third parties. Many of these interoperability challenges remain unresolved. When it comes to buildings and energy systems within them, it is uncommon to find a building where all energy-consuming systems can communicate seamlessly and continuously transmit data to a centralized hub at the building level where such a hub would enable intervention and control over these systems to optimize their performance. However, if energy systems in buildings are managed separately and categorized based on the level of control occupants have over them, it would help in defining acceptable deviations from predicted energy performance and thereby improve overall energy prediction. To achieve this and avoid overly optimistic predictions in the design stage which is acknowledged to be one of the causes that contribute to the EPG, the introduction of system-level DTs is essential to simplify energy management in buildings.

The first step in applying this concept is categorizing energy systems based on the degree of occupant control over them. The EPG at the building level is distinct from the gap at the system level. An energy analyst might assume that equipment such as chillers or boilers are properly manufactured and operating within their specifications, making their performance predictable to some extent. However, this assumption does not apply

to the EPG at the building level for several reasons. For instance, deviations between in situ measured and simulated thermal resistance and transmittance are commonly observed, and these can be twice the predicted values (Asdrubali et al., 2014; Johnston et al., 2015). This indicates that early design stage assumptions regarding thermal resistance and transmittance may not reflect reality even if a building is constructed according to design specifications. If energy systems perform within specifications, this identifying hidden sources of EPG whether such as the building fabric or occupant behavior. By considering a building as a single entity or a system that comprises of many sub-systems, it is possible to decompose that entity into various sub-entities or sub-systems using a physics/engineering-based approach. This decomposition approach involves leveraging well-calibrated sub-models to manage overall energy performance prediction to identify which systems are less predictable and contribute more to the EPG thus allow research efforts to focus on them.

As mentioned earlier, the first part of the framework focuses on the design stage, illustrating how simulation tools could be used to mitigate the factors contributing to the EPG. While the second part focuses on the operational stage by exploring how to simplify and accelerate the adoption of DTs and DS with an emphasis on the type of data required from each model and how it will be utilized. The first step in creating this framework is proposing a unified methodology for quantifying the Energy Performance Gap (EPG), rather than simply comparing predicted (computed) and measured energy consumption and selection of relevant energy benchmarks. In the UK, for example, current benchmarks are based on average measured values from various buildings, regardless of whether they are energy efficient or inefficient. A more refined benchmark could be developed by using data exclusively from energy-efficient buildings. One potential source for such a benchmark in the UK is the quantitative measured energy performance data from buildings featured in the "Building Performance Awards," an event hosted by the Chartered Institution of Building Services Engineers (CIBSE), which highlights energy-efficient buildings. This approach would ensure that the benchmark for quantifying the EPG is based on the average performance of energy-efficient buildings. Two key reasons underscore the need for a unified methodology to quantify the EPG before developing the first framework:

1. Simulation tools could be viewed as a potential source to explore different design ideas to achieve intended energy targets.
2. Provide clarity on the magnitude of the EPG to answer a critical question whether the its widening or narrowing in response to intensive research efforts.

During the design stage, it is essential to obtain aggregated simulated energy performance data both at the building level and for each energy system, which can then be used in the operational stage to create a building-level DS and system-level DTs. The use of energy simulation tools should extend into the construction phase, allowing for necessary updates to the model based on changes made during construction. The simulation model should be continuously updated (calibrated) based on construction changes and the availability of ground-truth data to reduce the reliance on assumptions. This data is then utilized in the commissioning stage to create a building-level DS and system-level DTs of its systems, serving as valuable training data. Unlike the case DTs, operational data should not be fed into the building-level DS at a constant-pace. However, this should be achieved or decided at appropriate intervals for each building based on changes in operational requirements and climatic conditions. Once new/updated energy management techniques are developed by the building-level DS, DTs should be updated accordingly as energy management techniques are initially developed utilizing training data obtained from simulation tools and are not based on ground truth data.

At the time of writing, it remains highly difficult to create a DT of a building that fully encompasses all features of a real DT, as outlined in table Four. To overcome this challenge, the authors adopt the approach proposed by Ghorbani and Messner (2024), which categorizes DTs based on relationships and connectivity. In this context, the third category in table one is adapted and modified, where “multiple DTs converge on a single physical twin”

is modified to multiple DTs converge on a single DS. However, it must be acknowledged that, at the building level, there may be challenges with labeling this as a "building-level digital shadow," especially if some data from the DTs is manually inputted to the DS due to interoperability issues. Finally, data flow from the DS to the different DTs is achieved manually, as the data flow in a DS is typically from the physical to the digital counterpart, not vice versa. In the context of the proposed framework as shown in figure one below, the main role of the DS is to plan and strategize the achievement of intended energy targets, while the DTs of the different energy systems serve as means to achieve and realize those targets.

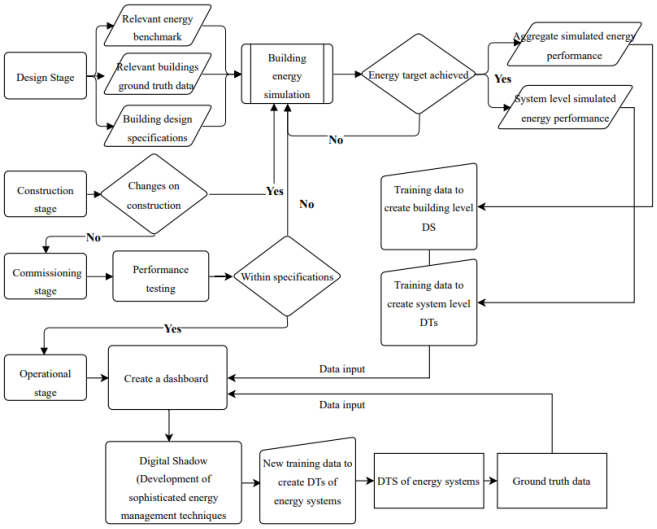

Figure 1: Framework for the mitigation of the EPG through utilization of simulation data to enable creation of building-level DS and system-level DTs.

DISCUSSSION AND CONCLUSION

This paper explored two well-recognised issues related to the energy analysis and lack of monitoring associated with the EPG in buildings while also addressing other challenges associated with the adoption of DTs. This research aims to serve academic community and industry professionals in addressing several key issues concerning the EPG and DTs:

- It outlines a potential method for standardizing the quantification of the EPG.
- It facilitates testing the viability of different solutions proposed to manage the EPG more effectively. By enabling researchers to more easily correlate quantitative measured energy performance data from literature, helping to answer two critical questions regarding the EPG:

1. What is the magnitude of the EPG?
2. Is the EPG widening or narrowing in response to intensive research efforts?

- It positions energy simulation tools as valuable tools for achieving energy targets and mitigate the EPG.
- It introduces the notions of building-level DS and system-level DTs to accelerate the adoption of DTs.
- It provides a concise yet accurate description of the six main features of 3D models, BIM models, DTs, and digital shadows, addressing a well-acknowledged issue observed in the literature.

The proposed framework in this paper is part of a novel PhD project that explores the potential of DTs and Outcome-Based Policies to mitigate the EPG. Future research will focus on demonstrating the framework by conducting a case study of an office building where the potential of DTs will be explored from the lens of a DS utilizing various toolkits of a DT platform. The framework will be validated through a comparative analysis approach. Four types of measured quantitative energy performance data will be obtained as follows:

1. Simulated energy performance before utilizing the DTs platform whether it's based on compliance or performance modelling.
2. Measured energy performance data before utilizing DTs platform.
3. Measured energy performance data after utilizing DTs
4. Relevant quantitative data from literature.

A comparison is firstly made between simulated and measured energy performance before utilizing DTs platform to quantify the EPG. In the second scenario, the predicted energy performance is compared against measured after utilizing DTs. Then, the results from first and second are compared to demonstrate whether DTs had a role in narrowing initial observed EPG down and how significant the mitigation of the gap. Final comparative analysis is made between measured energy performance data after utilizing DTs and quantitative

data of relevant case studies explored through literature. The selection of case studies from literature will be based on the method obtaining simulated energy performance of the case study conducted whether a comparison was between a compliance model against measured energy performance or a calibrated model against measured energy performance.

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