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Evaluating Digital Twin light quantity data exchange between a virtual and physical environment

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Abstract

Building Information Management (BIM) and Digital Twin (DT) technology can optimise lighting to support human health and well-being and the building's energy performance. The data exchange between a physical and virtual environment was investigated, focusing on a scenario in which optimal interaction between daylight and electric light derives an optimised realisation of a given light demand curve. Investigation and validation of a DT model were done using a virtual room simulated in DIALux Evo and its physical twin for three levels of geometrical complexity. The results show the influence of model complexity and consequences on the speed of information exchange.

Introduction

The built environment can impact human health and well-being daily through various factors. The light environment is one factor that strongly influences visual performance and comfort as well as mood, behaviour and interaction with the surroundings (Altomonte et al., 2020). For example, the recommendations of Brown et al. (2020) revealed that rooms with optimised light, both natural and electric, can improve several health outcomes. Building Information Modelling and Management (BIM) allows the architecture, engineering, and construction (AEC) industry to move forward from traditional working methods to a more digitalised way of working. It enables general improvement and optimisation of the built environment and lighting in particular (Skondras et al., 2019).

Computational light modelling is a technology used to design and analyse lighting, even though research has shown that lighting designers and architects do not commonly use these tools (Davoodi et al., 2019). A light simulation does not use any form of automated data exchange between the physical object and the digital object (Kritzinger et al., 2018). Additionally, it does not integrate real-time data to cope with regular changes in real life, nor can it immediately or directly affect the physical entity (Lu et al., 2020, Tao et al., 2018).

By implementing an Internet of Things (IoT) architecture in the BIM process in different phases of the building lifecycle, 3D virtual models with engaged as-built physical assets can be created (Skondras et al., 2019). This simulation approach is referred to as a Digital Twin (DT). Lu et al. (2020) defined a Digital Twin (DT) as "*a digital replica of physical assets, processes and systems. DTs integrate artificial intelligence, machine learning and data analytics to create living digital simulation models that are able to learn and update from multiple sources, and to represent and predict the current and future conditions of physical counterparts (p.1)*." Negri et al. (2017) added that sensed data, connected smart devices, mathematical models, and real-time data elaboration could optimise lighting design, predictive analytics, self-operating initiatives, and maintenance. The definition is based on preceding research (e.g., Garetti et al., 2012) and is used by many others (e.g., Kritzinger et al., 2018, Lu et al., 2020, Tao et al., 2018).

A DT can be defined by three levels of integration (Kritzinger et al., 2018). The first level is referred to as the Digital Model without any automated data exchange, and it equals the traditional light simulation. The second level implements a one-way automated data exchange between the physical and virtual world, called a Digital Shadow. It only becomes a Digital Twin when a two-way automated data exchange is established (see Figure 1).

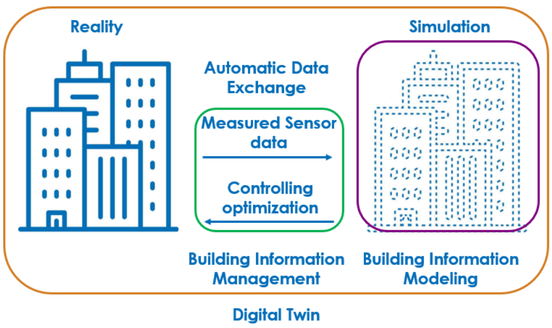

Figure 1. Building Information Modelling and Management, framed in purple and green, represents where it is used in the DT context. The bidirectional feedback in the DT concept shows the third level of integration (after Skondras et al., 2019).

A real-time data exchange means that sensor data is exported from real life, processed in a simulation tool in DT and later optimised, giving 'orders' to the lights in real life to change light level. It demands lighting technology, e.g., smart, intelligent, dynamic, or adaptive lighting and sensoring, in the built environment for control and communication. It enables lighting adjustment according to the lighting demand for optimal visual comfort and physical and mental well-being by providing the right amount of light at the right time of day (Abd-Alhamid et al., 2019, Brown et al., 2020). A so-called 'demand curve' can be created, which provides which quality and quantity of light exposure are required for human health, well-being, and comfort. Additionally, lighting technology that regulates the use of electric light only when needed will save energy (e.g., Mead, 2008, Hafezparast-Moadab et al., 2021).

Designing the illumination of a real environment has always been a complex and often tedious task, requiring much time and effort to manipulate, i.e., physical light sources, shades, and reflectors (Loscos et al., 1999). Lighting simulation is challenging due to the strict requirements to represent reality and, at the same time, provides different degrees of complexity for diverse users within the same field (Ochoa et al., 2012).

Since a DT partly represents reality, it should have a high level of detail (LOD) with as-built geometric information like size, shape, location, quantity and orientation and non-geometric information like material, light colour temperature, luminous flux (Latiffi et al., 2015). The realism is critical in lighting, where it directly affects the tested environment instantly compared to thermal and acoustic conditions. Furthermore, parametric BIM objects enable the data exchange process to be fully automated in DT. In other words, having one BIM model rich in information that later can be used in different simulation tools depending on its purpose will save time and effort and increase realism and accuracy. Nevertheless, every step of transferring data from one model format to another in creating a DT may introduce an error factor because of interoperability issues and the way it is performed (Gupta et al., 2014).

The enormous amount of information contained in BIM models will result in complex virtual environments. The increased number of sensors sending out continuous measurement data results in Big Data sets. The unstructured data requires a series of programming techniques to filter and map it. Big Data Analytics processes relevant data to convert it into practical and understandable information, which are tools for building management, optimisation, and decision-making (Lim et al., 2020, Ward and Barker, 2013). Visualisation of data is often used as a relatively simple way to ensure that more people understand what they see. For example, besides having the sensor data measuring illuminance values in a table or grid points, it is also informative to visualise the light distribution in the measured area showing luminance received by the eye and possible glare areas.

However, validation of light simulations has been done numerous times. Still, not many studies have investigated a digital twin-driven lighting simulation evaluation. Furthermore, there is a challenge in offering DT services in a single environment because some services need a 3D graphic interface (i.e., luminance distribution) while others can analyse data without a visualisation. A fully detailed BIM model has the advantages of realism and as-built information but the disadvantages of heaviness and complexity that can slow down the data exchange. On the other hand, a simplified BIM model will be easier to manage and serve the simulation purpose but may sacrifice accuracy. Therefore, the study investigates how the level of geometrical complexity of the virtual environment impacts time- and error factors during data exchange with the real environment with daylight and electric lighting for a given light demand curve.

Methods

The research methodology is based on a quantitative case study approach.

Setting

A case study was performed in a controlled laboratory apartment environment with smart lighting (Philips Hue bulbs and Bridge) and several illuminance sensors (HOBO Pendant MX2202) in Jönköping, Sweden (57°46′58″N 14°09′38″E). The test room had two large windows oriented towards North-East, allowing direct sunlight to enter the room only in the early hours of the day. The window in the bedroom part was covered with a black-out curtain limiting light to enter. Daylight illuminance values measured in the physical environment, the real twin (RT), were compared to values calculated in the DT, created using the DIALux evo (version 9) lighting simulation tool. Sensors were placed at different heights depending on the furniture height and both twin models used the same seven sensor points (see Figure 2). Since the simulation model's level of accuracy may impact the speed of data exchange, three models with varying geometric complexity were created: fine, medium, and coarse.

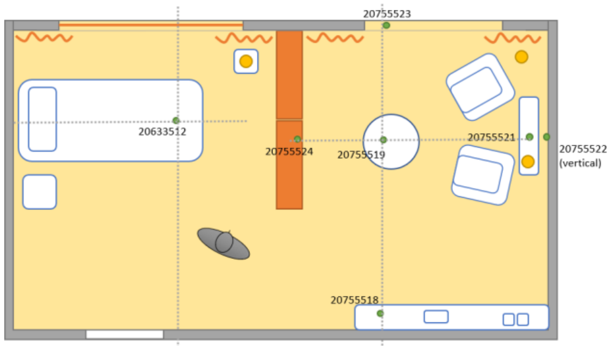

Figure 2. A schematic floor plan of the laboratory apartment showing the placement of the furniture, the seven sensor points (green dots, horizontally placed except one), and the three light sources (yellow dots). The room has two windows, and the bedroom window was screened.

Additionally, a simple lighting demand curve, specifying the light exposure (illuminance in lux) per hour for one day, based on (melanopic daylight equivalent illuminance) recommendations by Brown et al. (2020), was applied to the case, see Figure 3. The aim was to satisfy the human exposure demand as much as possible with daylight and use the DT to support a scenario for optimal interaction between daylight and electric lighting. Vertical illuminance (in lux) values were used for the light exposure data exchange between the RT and DT. Electric lighting is dimmed up and down appropriately based on the need for lighting. Optimization is reached from a human health perspective, serving right light at the right time and sustainability perspective, using as little energy as possible.

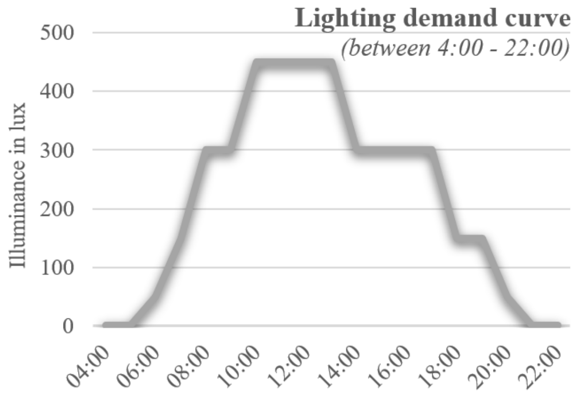

Figure 3. The applied curve for the human lighting demand (in illuminance in lux per hour between 4:00 and 22:00), based on melanopic daylight equivalent illuminance recommendations by Brown et al. (2020).

Procedure

Creating a DT started with using a BIM authoring software application (Revit) based on a point cloud file created by photogrammetric laser scanning equipment of the real environment. Then, a fully parametric BIM model with a high level of detail was exported in Industry Foundation Classes (IFC) format to the lighting simulation tool (DIALux evo) to perform lighting analysis. The BIM-models applied were Author Design Model and Review Design Model in Revit and Analyse Lighting Performance in DIALux evo. Due to interoperability issues between two software tools, much geometrical information regarding furniture and lighting fixtures got lost. Non-geometrical information such as colour temperature and luminous flux did not follow into the simulation model either. The model was largely manually recreated in the simulation tool and the luminaire information was manually added. Real-time data for two dates (March 12th and 17th) were selected as those days represented a day with an overcast and clear sky condition, respectively. Comparisons were performed for the full 24 hours of each day. Next step was adding the sensor points and instead of taking only one point, in the DT a surface area was used to avoid mistakes due to misplacement of sensor points. As said, three copies of the simulation model were made with different levels of detail (see Figure 4). The very detailed fine model (f) was a level-one Digital Model that includes as-built objects (Kritzinger et al., 2018). The medium model (m) had main objects such as furniture and openings, but complex objects with many surfaces were removed, such as plants, curtains, and bed sheets. The coarse model (c) included main objects with simplified surfaces such as cylinders for circular tables and boxes for rectangular tables and armchairs. All detailed objects were removed. All models included the same luminaires and light sources. Next, the ratio between the simulated data in all three models and real-life data was calculated.

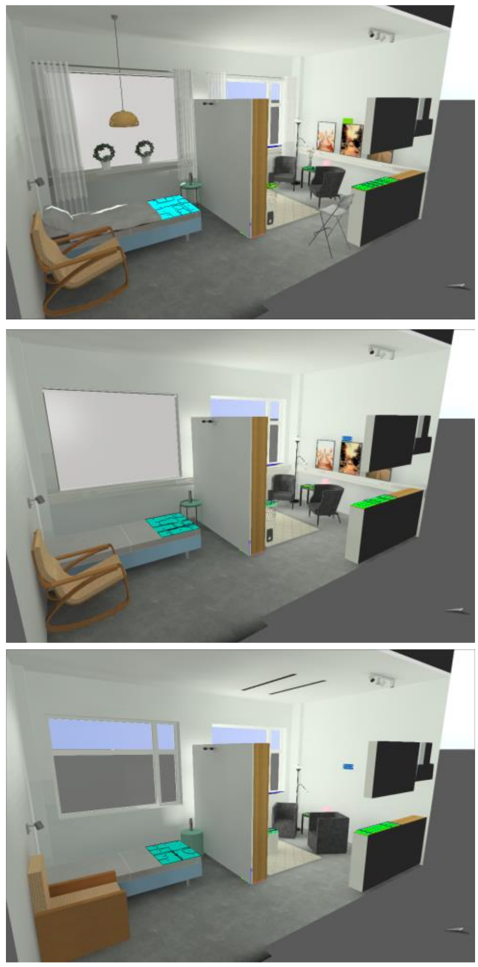

Figure 4. Three geometrical complexity levels of the DIALux simulation model: fine, medium, and coarse, respectively.

The final step was demonstrating how the DT and Real RT work together to reach the optimal solution for realizing a lighting demand curve (see Figure 3). It was done for the vertical sensor point in the space behind the chairs in the living room (see Figure 2). Based on the agreement of simulation data and demand curve data meeting the human needs, the difference between demand curve illuminance values and simulated values was calculated. By that, the required amount of electric lighting was determined. Then, the same simulation was run, predicting the daylight situation five minutes into the future. The DT calculated the optimal luminous flux needed to reach demand values while not exceeding it and wasting energy. This was done by turning the electric light source at different dimming levels.

Results

First, the comparison between the Real Twin and Digital Twin models is described and subsequently, the consequences for the data exchange and the light environment optimisation are shown.

Comparison of Real and Digital Twin

The simulated results were compared to the real-time sensor data. In **Error! Reference source not found.**, the data for only one sensor point are presented. The vertical sensor point close to the two chairs in the living room was selected to simulate the (demanded) light at the human eye (vertical plane). The figure shows the comparison of the RT and all three models for daylight illuminance values between 7:00 and 17:00. For the overcast sky condition (March 12th), the agreement between the RT and VT was, on average, 52, 62, and 63% for the fine, medium, and course models, respectively. However, the figure clearly shows the shifted peak and the higher daylight amount during the day for the RT. Disagreement between RT and DT for the clear sky condition (March 17th) was even more spread.

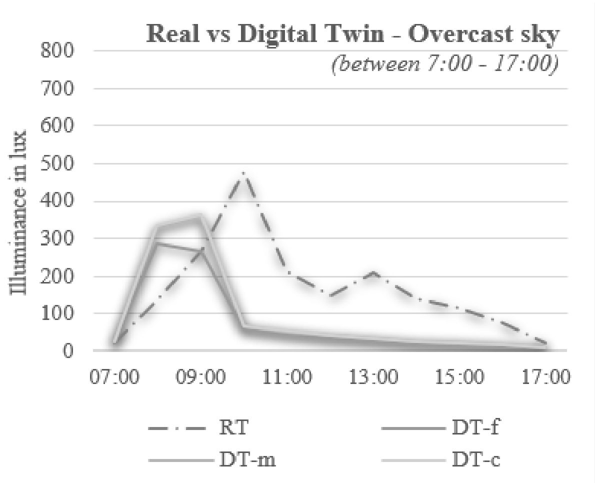

Figure 5. Comparison of real-time data in the physical environment (RT) and simulation data from the fine (DT-f), medium (DT-m), and coarse model (DT-c).

Optimization of data exchange

After applying the three levels of geometrical complexity, the average simulation time was calculated manually. Table 1 summarises the results for when the full model was calculated and when the calculation surfaces only were considered. Overall, the average calculation time for the clear sky condition took slightly longer than the situation with the overcast sky condition. As expected, the coarse model had the fastest simulation time, both for the full model and surfaces-only calculations. The higher the level of complexity, the longer time it takes to simulate. Calculation of surfaces only for the fine model reduced the calculation time to 1/10th of the original time for the fine model, whereas this reduction was 1/3 for the coarse model. Both the 'full model' and the 'calculation surfaces only' options provided the same illuminance values, indicating that the surface calculation option has high accuracy and fast results. It can be a choice when illuminance results are only presented as values, not for visualisation or rendering.

Table 1. Average calculation time (in mm:ss.0) for the three different Digital Twin models (fine, medium, and course) for two different sky conditions (overcast, clear) between 7:00 and 17:00 when including either the full model or just the calculations surfaces.

		Calculation time	
		Overcast sky	**Clear sky**
DT-fine	**Full model**	05:16.3	05:17.9
	Surfaces	00:29.1	00:29.9
DT-medium	**Full model**	02:03.6	02:05.2
	Surfaces	00:23.6	02:05.2
DT-course	**Full model**	01:02.8	01:00.6
	Surfaces	00:19.6	00:19.8

Optimisation of light environment

For one chosen point, the vertical sensor behind the chairs in the living room, the interaction between the RT and VT was explored when realising the lighting demand curve (Figure 3). For the VT, the course model was used. The amount of daylight (DL) was collected (RT-DL) or calculated (DT-c-DL) and compared with the demand curve. If the daylight amount was insufficient, electric lighting using Light source 1 (L1) was used. The light source was dimmed down accordingly to match the demand curve as close as possible. If the illuminance from L1 was not enough, support from Light sources 2 (L2) or 3 (L3) was added. The maximum illuminance the light sources delivered was 90 lx, 50 lx, and 300 lx, respectively, for L1, L2, and L3. Figure 6a shows the dimming percentages of three light sources for the situation with the Real Twin (RT-DL) and Figure 6b shows the results for the course model Digital Twin (DT-c-DL). The dark grey line in both figures shows the resulting demand curve (Demand-res) which is higher around 10:00 for the RT and between 8:00 and 10:00 for the DT due to a high daylight supply.

The next step was a five-minute future prediction simulation using the light sources in the coarse DT model. With an hourly illuminance adjustment, the level is kept at a constant level for a full hour; see the example in Table 2. One hourly time step is used here as example: for the

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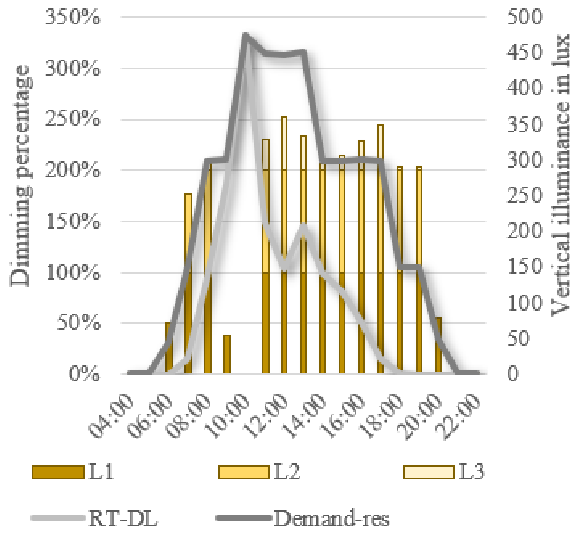
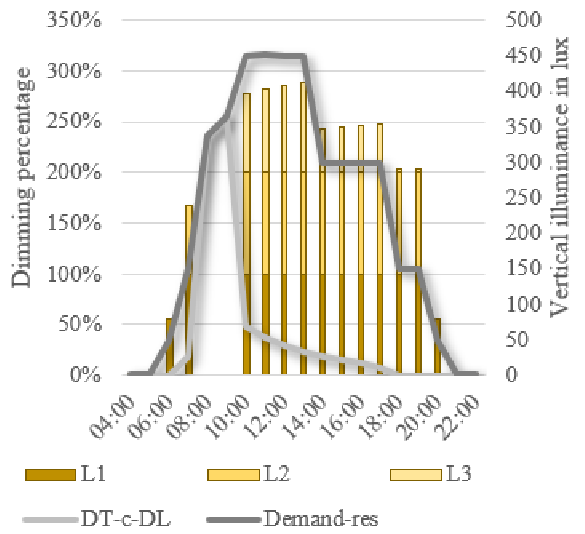
situation between 13:00 and 14:00, L3 is held at 34% and the two other sources at 100%.



a.



b.

Figure 6. Dimming percentages of three light sources (L1, L2, and L3) as a response to the daylight vertical illuminance (DL in lux, overcast sky, light grey line) to realise the Demand curve (dark grey line) for the situation with the Real Twin (RT-DL, figure a) and course model Digital Twin (DT-c-DL, figure b).

The DT 'knows' that the date for this simulation is March 12th, where - for this room and this orientation - the light level will slowly decrease between 13:00 and 14:00 with approximately 5.7 lx per five minutes (pre-knowledge/ calculated in the model). Hence, the DT can calculate what happens on average regarding the daylight situation at the moment when the RT sensor input comes in as well as five minutes in the future. It calculates then how much electric lighting is required for a *more optimal* light condition according to the demand curve. As said, Table 2.shows that L3 was turned on at 13:00 at 34%, delivering 451 lx. At 14:00, the light source had to be dimmed down even further, to 7%. With an hourly time-adjustment and no future adjustment, the electric lighting will keep the illuminance level at 451 lx until 14:00. The illuminance amount could have been reduced significantly with a shorter adjustment step and future adjustment, implemented by the DT.

Table 2. Example of the dimming situation for the three light sources (L) in the DT-c model between 13:00 and 14:00 on March 12th (overcast sky) and the agreement between the demanded and resulting illuminance level.

Time	Demand [lx]	L1	L2	L3	Demand-res [lx]
13:00	450	100%	100%	34%	451
14:00	300	100%	100%	7%	301

Discussion

The case study investigated the agreement between the RT and DT and the influence of the geometrical complexity of the DT model on accuracy and calculation speed. Additionally, it studied the optimisation between daylight and electric light in case the RT and DT interact. In this study, the DT manipulated the virtual environment in the simulation tool (digital model) manually instead of automatic programmed data exchange according to the Level of Integration (Kritzinger et al., 2018).

Comparison of Real and Digital Twin

The RT and DT (simulation) agreement was not very high, particularly on a day with a clear sky. The simulation model assumed that the sky was entirely overcast or clear for the whole day. In DIALux evo, the horizontal illuminance for a sky model cannot be set or adjusted besides the fact that, in reality, days may not be entirely 100% overcast or clear either. Additionally, assumptions have been made regarding the content and surroundings of the investigated room, and this shows the importance of having as-built BIM models (Latiffi et al., 2015). If more specific information was available, it could limit the chance of introducing errors in the process of DT creation. Since DIALux (evo) was initially developed for electric lighting simulations and has limited capabilities regarding daylight simulations, it may explain the difference in light amounts, especially as a result of direct reflections in adjacent windows when there is a clear sky condition.

However, DIALux evo and Revit are simulation tools that lighting designers and architects frequently use. In the operation or facility management phase of the building's life cycle, building performance analyses are often performed (re-)using BIM models received from previous building cycle phases. Ideally, data can be exchanged automatically between the BIM design model and the lighting simulation model to avoid doubling the work of recreating the model in the simulation tool. However, in this study, the BIM tool and the simulation tool had interoperability issues that could not be controlled, resulting in doubling the amount of work, time, and effort to recreate/reuse a simulation model. For example, furniture objects and lighting fixtures placed in Revit did not appear in DIALux evo and had to be replaced in the lighting simulation tool. Even when objects were imported directly into DIALux evo from other software tools like SketchUp, the dimensions were distorted and needed manual manipulation.

The used lighting simulation tool did not support other file formats and had a limited library of objects, which is one of the challenges faced when implementing new technology in traditional working methods (Skondras et al., 2019). In most cases, BIM systems at companies are equipped with conventional tools for light simulation (e.g., DIALux evo, Velux Visualiser, Revit Insight 360). However, these tools need to be updated and completed with intelligent devices (e.g., sensors, weather stations, smart light sources) and programming (to connect the physical world with the virtual world) to cope with DT technology (Macchi et al., 2018).

Optimization of data exchange

As expected, the comparison between the three geometrical models showed that the model with the lowest geometrical complexity had the fastest simulation time. However, unexpectedly, the model with the lowest level of geometrical complexity showed a better agreement with the real world. An explanation can be that the coarse model was predominantly developed directly in DIALux evo. For example, instead of using a BIM model for a chair, a standard box in DIALux evo was placed in the room.

Not surprising, the average calculation time for the condition with a clear sky and higher illuminance values (March 17th) took slightly longer compared to the situation with an overcast sky condition (March 12th). It is likely because a clear sky simulation combines direct and diffuse light calculations, while a model using an overcast sky has only diffuse light calculations. The calculations were relatively fast in all cases: less than 6 minutes for the most detailed full model. However, the method described was simplified and focussed only on illuminance values. In case of full high dynamic range images, required for, for example, visual comfort analysis as a significant part of integrative lighting solutions, the calculation time will be much longer.

Optimisation of light environment

During the RT and DT interaction, the DT plays a crucial role in finding the optimal lighting as a combination of daylight and electric lighting for human well-being and energy saving. The results showed that, in theory, the interaction between the RT and DT can create a light condition that agrees with recommended values. This study used a simplified version of general light recommendations (Brown et al., 2020). However, different tasks require different lighting conditions, and therefore, it is essential to use appropriate demand curves when presenting different scenarios of daily activities. Nevertheless, for realising actual integrative lighting, the light amount and spectral and spatial distribution of the light are crucial. They are supplied at the appropriate time of the day.

The fast simulation time and the continuous measurements of real-time data allow a DT to test and control alternatives in the virtual environment before sending information to the RT, predicting what may happen in the near future. For example, when the DT simulated five minutes in future at 13:00, electric light was more than enough at 34%. Therefore, the DT can simulate and explore a 33% or even 32% lamp dimming condition to reach the optimal required light levels. When a DT predicts a need for increasing light levels, it can send information to RT to turn on electric light gradually to reach better visual comfort. Instead of testing each light level in DT and sending data to the RT, testing all different light level alternatives in a virtual world and finally choosing the best option will save a lot of energy. This process can only be done with future predictions and requires high calculation speeds.

Conclusions

Researchers and practitioners are becoming more interested in the DT application in the AEC industry in recent years. This paper explored a digital twin-driven lighting simulation and optimised characteristics for data exchange between a physical and virtual light environment. The light environment was optimised for an interaction between the RT and DT. Slightly against expectations, the results showed that the coarse model was a more accurate representation of the physical environment and generated faster data exchange. Calculations required for appropriate data exchange between RT and DT were fast in all investigated cases. However, the method described was simplified, and future studies should explore more complex situations, including, for example, high dynamic range image calculations. Furthermore, the results showed that, in theory, the interaction between the RT and DT can create a light condition that agrees with recommended values. Future studies should apply and test multiple appropriate demand curves presenting different scenarios of daily activities and include requirements for spectral, spatial and temporal light distribution.

Acknowledgments

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