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The use of synthesised data for the development of Digital Twin: Chalmers student house case study

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Abstract. This research focuses on the development of a digital twin for a residential building using a synthesised data approach. The methodology involves five stages, with three of them dedicated to simulating different energy scenarios: actual energy consumption, passive house level consumption, and consumption after the implementation of smart building technology. The selected building is located at the Chalmers Technical University campus in Sweden. Synthesised data is used to simulate the energy demand of the building before and after renovation, as well as after the implementation of smart building technology. A custom agent-based simulation model is developed to simulate the impact of residents' behaviours on the building's energy consumption, and high-resolution data was analysed and synthesised to create a new dataset that was applied to the selected buildings. Finally, the results of the simulations were analysed and compared to assess the potential energy savings and improved energy performance achieved through the implementation of different scenarios. The study provides insights into the energy-efficiency of different measures for reducing energy consumption in residential buildings. The study provides insights into the energy-efficiency of different measures for reducing energy consumption in residential buildings. This research shows the potential of using synthesised data to assess and forecast changes in building stock transformation, even when real data are not available.

1. Introduction

According to UN Habitat, 78% of the world's energy consumption is due to cities, which are responsible for more than 60% of greenhouse gas emissions and is expected to rise in the near future due to rapid urbanization. [1]. Considering that currently 55% of the world's population lives in cities [2], and that this number is expected to grow to 81% in developed countries by 2050 [3]. It has to be taken into account that the energy mix, climate and urban form are the main factors that determine the total energy consumption in cities [4-6] and that there is also an important correlation with energy demand [7]. As a result of the above and global warming, it is critical to think about the development of climate-resilient cities [8]. To meet energy-reduction goals, cities are challenged with assessing building energy performance and prioritizing efficiency upgrades across existing buildings [9]. Smart city digital twins, a recent endeavor to create a digital replica of city infrastructure linked to real-time city data, are envisioned to improve city monitoring, control, and decision making through enhanced visualization and interaction with city data [10]. The digital twin, as an inevitable trend of digital transformation, helps cities realize real-time remote monitoring, and allows more effective decision-making [11]. The digital twin can create a mirror of the building by combining graphical modelling and data storage in different resolutions [12]. With it is possible to connect scenarios, with past, present, and projected information. However, understanding the building or district performance requires a large amount of data and cross-disciplinary analysis. One of the main barriers is the lack of data to feed the digital city twins, especially tenants' behaviours data. This study presents a method to boost the development of digital twins with the use of synthesised data. It allows the further development of digital twins, anticipating the characteristics of the information, e.g., temporal resolution, spatial resolution, data disaggregation, etc. As well as anticipating the design of visualisation systems and scenario analysis.

Synthesised data has the potential to address this information challenge, in particular the need for detailed data on user behaviour, which is challenging to collect both due to the needed instrumentation as well as issues concerning privacy. According to IBM real data is generally too costly or time-consuming to collect and/or use and synthetic and synthesised data is easy to scale and collect for any usecase [12]. By creating a probabilistic model of resident behaviour and other key factors, data can be generated at scale with the needed resolution and can be used to drive further simulations of the digital twin. The main challenge is to ensure that the generated data is realistic enough. This can be achieved by comparing the model output with a set of measured data, and by careful study using expert knowledge. So-called "black box" models can be effective and time saving in some scenarios. Such models are trained from existing data without any manual input. However, they have significant limitations in that the parameters cannot be easily interpreted, or manipulated, which is necessary to simulate various scenarios, and it can be difficult to determine whether they have captured important relationships in the input data. For the use case at hand, an explicit model is more suitable, even though it is more time consuming to create, because it can be ensured that the relevant relationships are modelled in a reasonable manner.

2. Methodology

The research considers five stages for its development, three of which related to three main simulation scenarios: Actual energy simulation, Passive house level simulation and Smart building technology application simulation (Fig.1).

Stage 0: Case study selection

For this study was selected an area at Chalmers Technical University campus, which include several residential buildings (dormitory), as well as learning halls and industrial labs. But the main focus of this paper is on the residential building digital twin development with a use of both synthesized and synthesised data.

Stage 1: Simulation of current energy demand with synthesised data

During this stage the energy demand of the selected buildings were simulated using general descriptions of the building's performance and construction and synthesised data developed according to the data-driven occupancy profiles [13]. This simulation has been done using a building energy simulation software EnergyPlus [14]. The simulation was conducted at an hourly resolution to capture the variation in energy demand throughout the year. The results of the simulations represent the energy consumption of the selected buildings.

Stage 2: Simulation of energy demand after renovation with synthesised data

At this stage the energy demand of the selected buildings was simulated after it has been renovated to the level of current and passive energy standards in Sweden [15]. This can be done using the same building energy simulation software as in Stage 1. The results of the simulations represent the potential energy consumption of the selected building after renovation.

Stage 3: Smart building technology implementation with synthesised data

During this stage the smart building technology were applied to the selected buildings and simulate the energy demand again. The smart building technology portfolio and smart building operation patterns were extracted from another student house at Chalmer' Campus – HSB Living Lab. This real-life living laboratory use next smart building solutions: PV panels, energy storage, smart appliances schedule, shower cleans and recirculates water, VVC-Booster, Heat pumps, FTX-system. To accurately simulate the impact of smart building technology, it is necessary to have detailed data on residents' behaviours, such as individual usage of heating, home appliances, shower, etc. Since this level of detailed modelling is typically not supported by state-of-the-art building simulation software, a custom agent-based simulation model can be developed to simulate this behaviour. The model parameters are set based on expert knowledge and the accuracy verified by comparing aggregated building level consumption with actual measured data. The generated synthesised consumption data can then be fed into the building simulation software to increase the accuracy of building-level simulations using the modelled behaviour of the virtual residents. The parameters of the agent-based model can be altered to simulate different behaviours and other properties such as the efficiency of modern appliances. The high-resolution data related to energy usage and residents' behaviours patterns were analysed and synthesised into the new data set, which was applied to the selected for the simulation buildings. The results of the simulations represent the potential energy savings and improved building energy performance that could be achieved through the implementation of smart building technology.

Stage 4: Analysis and comparison of results
In the end, we analysed and compared the results of the simulations to assess the potential energy savings and improved building energy performance achieved through renovation and smart building technology implementation.

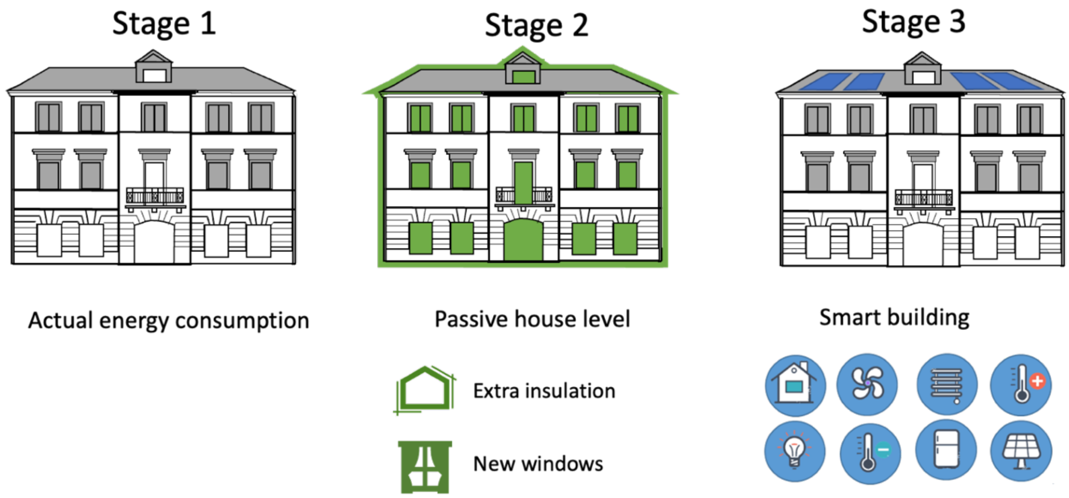


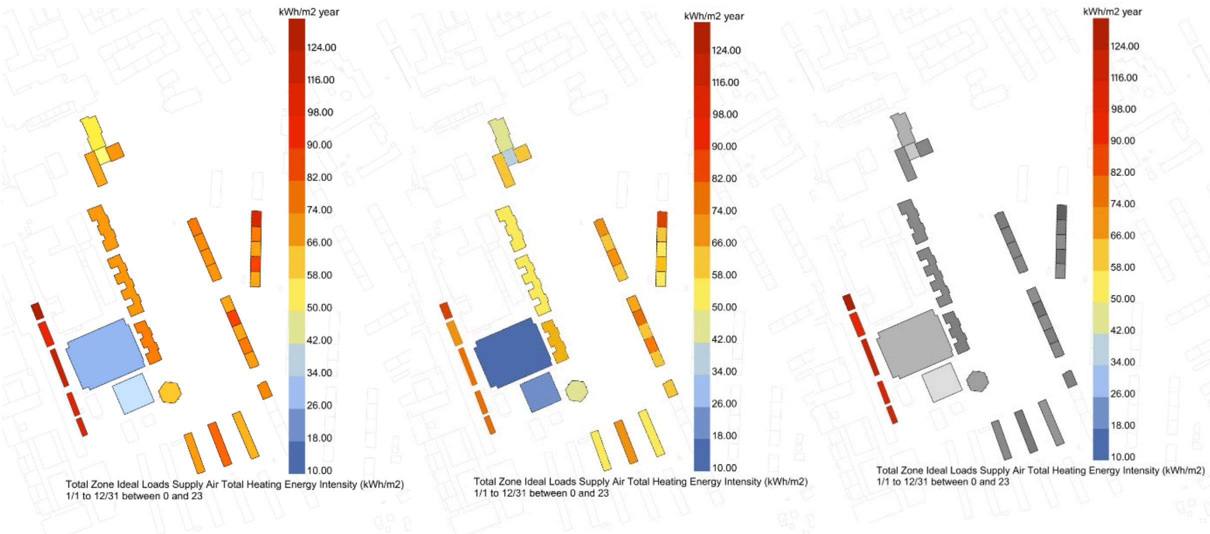
Figure 1. Three main simulation scenarios of the study: Actual energy, Passive house level and Smart building technology application

These results will enable the development of a scenario analysis and visualisation platform, identifying the necessary details in the data to comprehensively assess the different options and how these can be compared at different scales of intervention and their impact over time. This exercise allows to anticipate the levels of detail that are required to be incorporated into the Digital Twin, which allows to identify the investments that are necessary to obtain the expected results. It also allows to adjust and develop the technological and programming challenges without having access to the measurement data.

3. Results and discussion

The results show that indeed, renovating the envelope generates significant energy savings in the buildings, around 22% compared to the initial situation. The levels of reduction are mainly related to the size of the building and the category of the building, residential, office or educational. Another aspect that can impact on the performance of buildings is the access to solar gains during winter, and the obstruction of surrounding buildings. As is the case with student residential buildings, as they are surrounded by taller buildings and are within walking distance of each other.

In Scenarios 1 and 2, the schedules used to generate the synthesised data are identical, assuming that people exhibit similar behaviours before and after renovation. On each day of the year, six different patterns are used: occupancy, ventilation, lighting, room electricity (appliances), heating, and DHW. Each of these patterns fluctuates by 30% daily, meaning that seven hours of the day are randomly selected to vary their data, to replicate the stochastic behaviour of users while maintaining the hourly framework. The base patterns also modify their structure for weekdays and weekends, as well as throughout the year to reflect winter, spring, and summer. Figure 3 illustrates the calendar and profiles structures, along with the range over which each data point can vary, with an average range of +20% to -30%.



Stage 1 (base case) **Stage 2** (Passive house) **Stage 3** (Smart Buildings)

Figure 2. Yearly improvement of energy demand according to each renovation scenario

The results on energy demand demonstrate that the building's total energy demand for all services, including heating, domestic hot water, lighting, and electrical equipment in the base scenario (where the building does not consider any energy efficiency measures) is 220 kWh/m^2. Heating accounts for 64% (140.3 kWh/m^2), electricity including DHW for 24% (53.6 kWh/m^2), and lighting for 12% (26.9 kWh/m2). In scenario 2, where the building envelope is renovated to a passive house level, the energy demand corresponds to 184 kWh/m^2, with heating, electricity, and lighting accounting for 56% (103.8 kWh/m^2), 29% (53.6 kWh/m^2), and 15% (26.9 kWh/m^2), respectively. In scenario 3, where the original envelope is maintained, but sensors and efficient equipment are incorporated, the total energy demand is 196 kWh/m^2, broken down into 72% for heating (142.7 kWh/m^2), 18.9% for electricity (37.0 kWh/m^2), and 8.4% for lighting (16.4 kWh/m^2). These results indicate that a deep renovation of the building can reduce heating demand by 26%, which represents 16% of the total building demand. On the other hand, in the smart building scenario, the heating demand rises by 2%, as more heat is required to maintain the building due to the installation of more efficient equipment, which provides less heat inside the building. However, the savings in terms of lighting and electrical equipment are 11% of the total energy consumption. Comparing scenarios 2 and 3, it can be deduced that the difference in energy savings is only 4% of the total demand. Considering all the complications involved in deep renovation of a building, the option of only upgrading the building's equipment shows promising results.

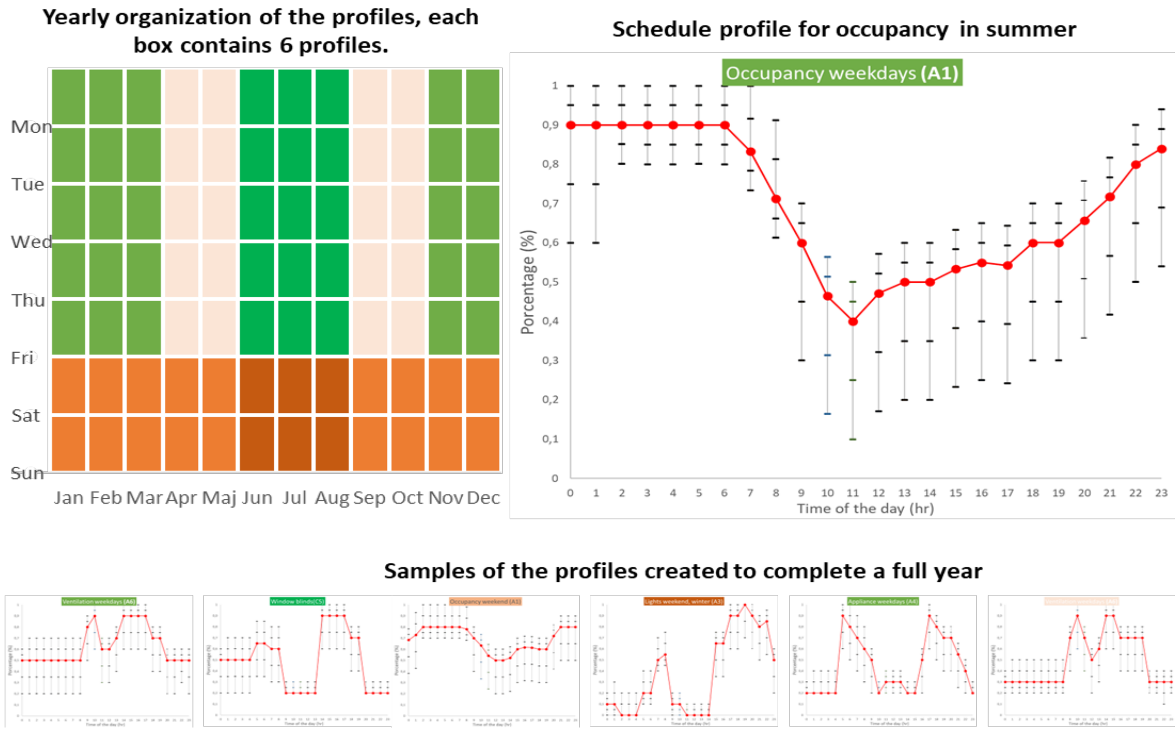


Figure 3. Samples of the schedule profiles used for the simulation and their distribution during the year

The results can be visualized in Figure 4, which presents each scenario and a breakdown of the total energy demand of the building by category. The results are presented for each hour of the day, providing average consumption data over the year. It is evident from the data that in scenario 2, the primary energy reduction is in heating. However, solar gains are reduced due to the upgrading of windows, which leads to a decrease in solar gains. On the other hand, in scenario 3, the behaviour of major consumption such as heating is similar to the base case, but with a greater amplitude during the night. During the period of user activity, i.e. between 8 am and 10 pm, there is a significant reduction in the rest of the energy consumption, with domestic hot water and electrical equipment having the most significant impact.

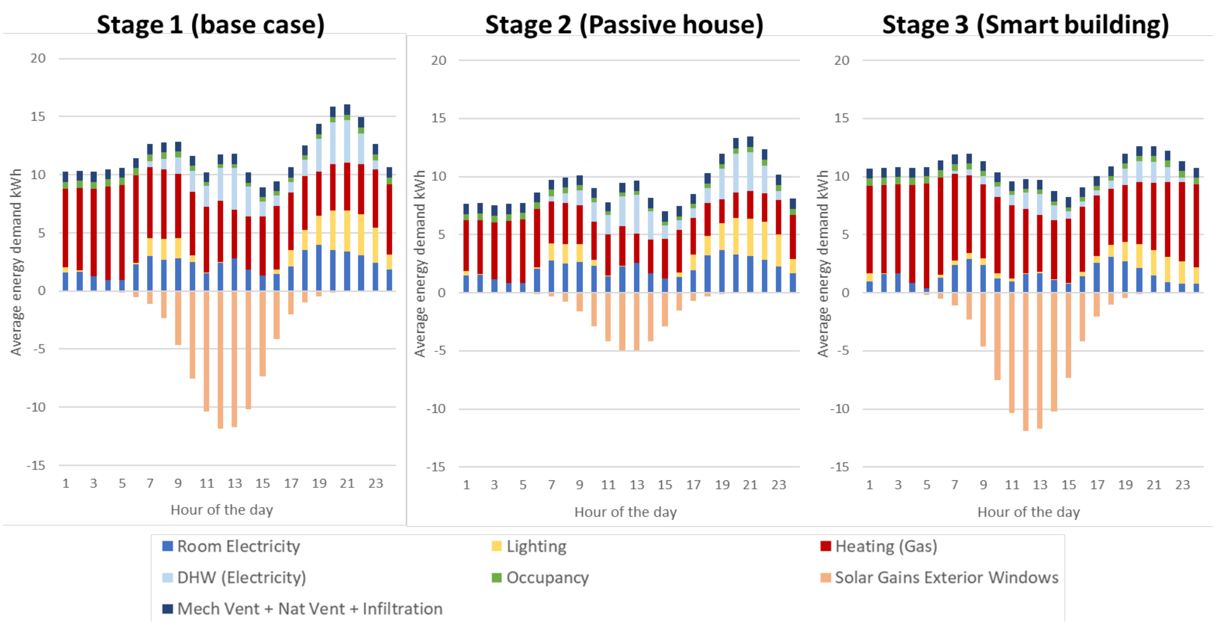


Figure 4. Breakdown of the total energy demand of the building by category for each scenario

4. Conclusion

The advantage of using synthesised data to assess and forecast changes in building stock transformation, even when real data are not available are that it is possible to anticipate what data will be needed to measure to make assessments. In our case, we have used data from mixed sources for the elaboration of the synthesized data, measured data from similar buildings, and results in the literature. As an exercise, it is interesting as it allows having a synopsis of possible solutions or designs to study, allowing researchers to dabble in data resolutions that are currently not possible to access.

However, the study presented has some limitations. Firstly, in scenario 2, the building's airtightness was not adjusted, which negatively impacted its energy performance. This is because there is no rate of improvement in air tightness after the renovation work. Additionally, the smart building scenario did not consider night-time temperature ranges (heating set-back point temperature), which also affected its energy performance. This is due to the necessary heating system changes that would make it challenging to compare with the base case reliably. Furthermore, the study did not consider the economic feasibility of the different scenarios, which is an important aspect to consider when implementing energy efficiency measures in buildings. Future research will be focus on visualization techniques for assessment purposes and improving the accuracy of the data used as inputs in the simulations. This work was further supported by the Swedish Research Council for Sustainable Development Formas under the grants 2019-01169 and I-Greta project by ERA-NET 2019.

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