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Mitigating operational greenhouse gas emissions in ageing residential buildings using an Urban Digital Twin dashboard

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A R T I C L E I N F O

Dataset link: https://ghg.app.frs.ethz.ch/

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A B S T R A C T

With the increasing stock of ageing infrastructure and resource constraints in Singapore, related risks and carbon emissions can be mitigated through long-term resilience planning, automated building inspection, and effective maintenance. Sustainable actions are needed to maintain Singapore's ageing infrastructure. Hence, a state-of-the-art control and management system is required in the form of smart city digital tools. We introduce an Urban Digital Twin (UDT)—GHG App for decision-makers in Singapore's operational building greenhouse gas (GHG) emission mitigation and decarbonisation initiatives. Based on multiple-criteria decision analysis (MCDA), a Potential for Intervention (PFI) map was created to rejuvenate the building system. Decision-makers can use this map to prioritise the rejuvenation of low-carbon building systems in the built environment. A heat map of the PFI results highlights which buildings need urgent rejuvenation based on critical parameters. The GHG App utilises this method to generate maps and enables users to modify parameter weights based on their priorities, automatically updating the map. Users can plan an intervention for buildings with higher PFI values once the map is generated. The GHG App provides interactive data visualisation of 119,872 features representing Singapore's built environment, including the context size of 6,785 existing residential buildings modelled and used to demonstrate the analysis results. Our research findings can contribute to the development of standards for accounting for operational GHG emissions, setting emission limits, and planning decarbonisation in the built environment sector.

1. Introduction

Data-driven applications that can assist in the effective management of cities are being developed as a result of innovative city initiatives across the world. Smart cities have humans, technology, and institutions as their three elements, with the environment, energy, transportation, safety, healthcare, and education being fundamental disciplines. City sustainability, infrastructure, quality of life, and service to the inhabitants are enhanced by smart city initiatives [1,2]. Creating a city-scale digital twin would allow all disciplines mentioned above to be integrated and improve system operability on digital platforms [3,4]. An Urban Digital Twin (UDT) consists of a city 3D model with a combination of physical assets, multimodal sensor data and a bi-directional automated dataflow. Furthermore, UDTs provide planning and decision support to cities in terms of infrastructure, administration, citizen engagement, and economic development. Numerous digital twin implementations have reflected upon the built environment with varied use cases [5,6]. Energy industries are still experimenting with digital twin technologies [7,8], but they provide several opportunities to stimulate the energy transition and achieve sustainable energy development goals [9]. Ghenai et al. [9] highlight that digital twins can simulate and analyse energy components and systems, as well as diagnose problems at a low cost, thereby accelerating innovation, building consensus, and reducing costs.

Most importantly, there is a need for methodologies that can help develop datasets to deliver UDT platforms for decision-making [10]. More use cases, along with its bottom-up methodologies, have to be tested to develop UDTs for comprehensive decision-making. To address

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this need, our research introduces a dashboard—*GHG App* (https://ghg.app.frs.ethz.ch/)—with the building operational energy use and GHG emissions dataset for the city of Singapore.

With the increasing stock of ageing infrastructure and resource constraints in Singapore, related risks and carbon emissions can be mitigated with long-term resilience planning, automated building inspection works, and effective maintenance. Sustainable actions are needed to enhance Singapore's ageing infrastructure maintenance. Existing building renovation strategies must include decisions that align with the national greenhouse gas emission targets while considering the building's operational and embodied emissions [11,12]. Consequently, a state-of-the-art control and management system is required in the form of smart city digital tools that can facilitate policy instruments [13,14].

Singapore's housing system consists of public and private markets, with the Housing Development Board (HDB) managing the public market [15,16]. Since 1960, HDB has built more than 1.2 million dwelling units in Singapore, and as of 31 March 2023, there are 1.1 million dwelling units under its management, with 77% of the resident population living in HDB flats [17]. Existing public housing buildings and towns are upgraded to enhance the living environment in and around residents' homes. Older flats commonly experience wear and tear, which is addressed by Home Improvement Programmes (HIPs). Direct lift access is offered to residents as part of the Lift Upgrading Programme (LUP). Over 500,000 households have benefited from the LUP since its launch in 2001. Additionally, the Neighbourhood Renewal Programme (NRP) continues to improve residents' immediate living environment. We use the term "rejuvenation" for buildings in this article for the reason that it encompasses both the actions of renovation and retrofitting of building systems to efficiently sustain buildings. In particular, we use the term rejuvenation because it is used in policies to represent programmes such as HIP, LUP, NRP etc. that help keep livability and vibrancy in public housing in Singapore [18].

Carbon dioxide (CO_2), primarily released when fossil fuels are burned to produce energy for the industry, construction, residential, and transportation sectors, is the most significant greenhouse gas (GHG) released in Singapore [19]. Singapore's GHG emissions for 2021 totalled 53.6 $MtCO_2e$ (million tonnes of carbon dioxide equivalent). In November 2022, Singapore set a new target of limiting GHG emissions in 2030 to 60 $MtCO_2e$, down from 65 $MtCO_2e$ in the previous submission of Nationally Determined Contribution (NDC) [20]. However, the Climate Action Tracker (CAT) continues to project Singapore's overall CAT rating as "critically insufficient" and far higher than 1.5 °C levels [21].

Singapore's hot and humid tropical climate leads to the majority of electricity use, fulfilling the great demand for cooling in commercial and residential sectors [22]. Singapore's total electricity use increased by 10%, from 49.6 TWh in 2017 to 54.9 TWh in 2022 [23]. In the power sector, natural gas replaced oil as the primary fuel after the early 2000s. In 2021, the share of the energy input in electricity from natural gas increased to 94.9% from 66% in 2005 [24]. Solar, biomass and municipal waste (referred to as other energy products) account for 2.9%. Petroleum-based products, mainly diesel and fuel oil, make up the remaining 1.0%, with coal making up 1.2% of the total. Solar energy is seen as an economical alternative energy option in comparison to electricity produced from fossil fuels. By 2030, Singapore aims to deploy 2 GWp (gigawatt-peak) of solar with the help of government initiatives and policies. However, the integration of a large deployment of solar PV into the smart infrastructure of the city energy systems, such as microgrids, district cooling systems and storage batteries, increases the complexity of operability, data processing, and optimisation.

In this article, we describe the UDT use case for estimating and mitigating greenhouse gas emissions in ageing residential buildings. In the following Section, we elaborate on the progress of UDTs that are dedicated to optimising the built environment and energy sector and decarbonising cities through relevant works in literature. Further explanation is provided as to how the proposed dashboard is unique in comparison to the existing examples found in the literature. Subsequently, we study the applicability of Multiple-Criteria Decision Analysis (MCDA) in City Planning, Environmental Science, and Sustainable Energy.

The methodology of our research is explained in four parts in Section 3. In Section 3.1, we demonstrate the conceptual architecture and user experience of UDT development that supports decision-makers and stakeholders. In Section 3.2, we present the use case that we developed based on the dashboard and elaborate on the method specific to estimating operational GHG emissions of buildings based on openly available energy use data. In Section 3.3, we introduce a method for simulating energy demand in case of missing energy use data and generate alternative scenario outputs using a forecasting method. In Section 3.4, we propose a Potential For Intervention (PFI) Map using MCDA with a future scenario (for the sample year 2040) of public housing to prioritise low-carbon building systems rejuvenation. Additionally, details are provided about the parameters included for creating a PFI map, the normalisation step of parameters of varying scales using the sigmoid function, the aggregation of normalised values, and the classification. Finally in Section 4, we discuss the results of GHG estimation and PFI along with parameters of varied user priority or input weights (see Table 6), followed by the conclusion (Section 5).

2. Related works

2.1. Urban Digital Twins (UDT)

Instances of UDTs dedicated to facility management, retrofitting, or operational optimisation [25–29] are frequently surfacing in smart city initiatives. In literature, however, a limited number of UDTs are dedicated to decarbonising cities and providing support to related existing policy instruments in cities [14,30,31]. Paiho et al. [31] highlight that there is a need for definite use cases with specific combinations of technology and policy aspects implemented in the built environment. Based on their study of Finland, they claim that the current EU policy mix [32–34] sets no clear goals for the digital transition and does not aim directly at influencing end users' conservation and efficiency behaviours. To promote green and digital transition in EU member states, it is necessary to assess whether digital transition aims and targets are compatible with existing and potential technological imbalances. A discrepancy in regulation and control instruments is widespread in various countries and towards their climate action [35–37].

The GHG App shares similar features as example projects from the literature, including Urban Strategy [38], TEDA [39], Cambridge [40], Digital Urban European Twins (DUET) [41], and the City of Zurich [42]. All the aforementioned examples address issues related to urban development (for instance, air and noise pollution, health, climate, emergency, operation, and management) with suitable applications and provide insights into alternative scenarios which can help stakeholders make better decisions to address the respective urban issues. However, the UDTs found in the literature vary in terms of the applications provided and the stakeholders for whom they are developed. The following are various applications provided by examples from literature: environmental pollution and emissions from transport by Urban Strategy [38]; emergency and crisis prediction by the spatial and temporal data platform for urban virtual simulation - TEDA (Tianjin Economic-Technological Development Area) New District, China [39]; building operation and maintenance application by the digital twin demonstrator for West Cambridge campus, UK [40]; air quality and noise emission application by the Digital Urban European Twins (DUET) project, Europe [41]; and density effects on urban climate and mobility study for the City of Zurich [42].

The example UDTs are based on disparate 3D data formats and frameworks, providing applications with varied levels of access to the public. For instance, both DUET [41] and Urban Strategy [38] provide environmental pollution-based applications within their UDTs, however, exclusively the DUET project provides open access to its dataset and application. The West Cambridge campus UDT [40] is developed for facility managers for building operation and maintenance. Both the TEDA New District [39] and Zurich city UDTs [42] are developed mainly for city planners as stakeholders. The DUET [41] and Urban Strategy [38] applications extensively target professionals and researchers both in academia and industry.

In comparison, the proposed GHG App is expected to support various stakeholders in facility management, city planning, policymaking, sustainable design and development, energy efficiency, etc., particularly those who are interested in decarbonising initiatives for cities and mitigation concerning climate change. A limited number of applications are dedicated to decarbonisation, accounting for operational GHG emissions and improving the energy efficiency of buildings, while being openly accessible to the public. For instance, Urban Strategy [38] is dedicated to decarbonisation through environmental analyses to mitigate transport-based pollution and emissions, however, the application and dataset developed are not fully open to public access. To improve maintenance procedures and energy efficiency and turn port areas into ZEDs (Zero Energy Districts), the digital twin of the Port of Anzio in Italy [43] provides open-source tools for renewable energy management systems. Their project is dedicated to the decarbonisation of port areas in Italy. Hence, it is linked to transport and does not extend its services beyond the port.

Huang et al. [8] propose a Cloud-based Integrated Energy Planning Studio (CloudIEPS), a conceptual digital twin-based energy internet planning platform. The authors demonstrate CloudIEPS with a case analysis for an optimised operation of energy internet for a future smart city in China. The demonstration provides an optimised solution that reduces one-time investment costs compared to the original scheme. Since CloudIEPS is a conceptual DT framework that deals with the specific use case of operation optimisation of integrated energy systems, it cannot be compared with the GHG App.

Urban building energy modelling (UBEM) tools such as City Energy Analyst (CEA) [44], CityBES [45], and UBEM.io [46] are dedicated to the decarbonisation of cities and are similar to the proposed GHG App for this objective. They help users such as urban design teams and municipal governments to create scenarios for future mitigation of GHG emissions in buildings. CityBES and UBEM.io are free web services that rely on big urban data sets in geospatial formats such as GIS and are combined with building energy models based on the same principles as those used to design or renovate high-performance green buildings. Similarly, CEA uses GIS datasets and includes building energy models to assess building energy performance in a desktop application.

City Building Energy Saver (CityBES) allows users to quickly set up and run UBEM to support city-scale building energy efficiency analysis. Chen et al. [45] presented CityBES with case studies in six cities in the United States that analysed energy use and cost saving of five individual energy conservation measures (ECMs) and measure packages for office and retail buildings. CityBES employs the Commercial Building Energy Saver (CBES) toolkit [47,48], which builds on energy simulation tools OpenStudio [49] and EnergyPlus [50] to deliver energy retrofit analyses of individual commercial buildings (offices and retail) in U.S. cities.

UBEM.io automates the stock-level generation and analysis of UBEMs for carbon reduction studies. UBEM.io takes an archetype approach to automatically assign simulation templates to buildings in the same categories with similar physical and mechanical representations. UBEM.io has a modular framework with an urban model generator module to help users generate building geometry using GIS files (user input) and uses a library with a pre-built building template for buildings in the United States and Irish building stocks. Then the model visualiser module compares multiple scenarios for carbon reduction. Ang et al. [46] presented UBEM.io and its framework tested for the City of Evanston, IL (USA), and conducted a workshop with representatives from eight municipalities worldwide.

Both CityBES and UBEM.io are built on the prerequisite dataset from city municipal records to generate energy models. On the other hand, the GHG App is built bottom-up with no conditional dataset required from users. The GHG App offers a comparison of individual buildings on a city scale and leads decision-makers to buildings that need urgent renovation. The GHG App is designed to help existing renovation policies and programmes and guide future renovation work. CityBES is limited to U.S. cities and commercial buildings. The GHG App offers analyses for all building typologies in Singapore, however, at present most datasets are available for residential and commercial buildings. We rely on the City Energy Analyst (CEA) to simulate the unavailable energy dataset and try to bridge this gap. The CEA tool was selected as it is also a bottom-up tool for physics-based urban building energy simulation at low computational expense. The tool has been well-tested in the Singapore context, including, among others, residential [51], commercial [52], university [53], and mixed-use districts [54,55], as well as urban-scale simulations [56]. In the GHG App framework, this UBEM is used to provide a simple estimate for buildings for which there is no other information. However, the GHG App framework and methodology for PFI analysis can in principle be applied and tested for other countries.

Deng et al. [57] systematically review the literature on the co-benefits of GHG mitigation as a result of documenting 1554 academic research articles and classifying the co-benefits into the types and sectors they belong to. The research finds that few papers study co-benefits in the building sector, and suggests that there is a need for research on GHG mitigation in the built environment. Our research [53,58–61] and the development of the tool dedicated to the estimation of GHG emissions try to fill the aforementioned research gap. The proposed use case represents a wide range of domains, including City Planning as a subset of Smart City initiatives and Planning Support Systems (PSS); Climate and Energy with its GHG mitigation policies; and Cyber-Physical Systems (CPS) with the Urban Digital Twin concept evolved from the conventional Digital Twin concept. The GHG App is distinctly unique as a tool in terms of its goal towards helping policy instruments for decarbonising cities, estimating operational GHG emissions of buildings, demonstrating what-if scenarios towards low-carbon building system rejuvenation in residential buildings and delivering open access to the created 3D integrated city energy dataset and application—*GHG App* (https://ghg.app.frs.ethz.ch/).

2.2. Multi-criteria decision analysis (MCDA)

MCDA is a set of mathematical tools and approaches designed to assist decision-makers and stakeholders in selecting the most appropriate solution to a given problem, based on the values of stakeholders and decision-makers, as well as technical information [62–64]. MCDA facilitates decision-making as a whole, as they allow for transparent analysis of competing criteria and competing interests [65–67]. The usage of the MCDA method for decision-making is found in various domains, including sustainable energy and environmental science [68,69]. MCDA helps to search for multiple preferences that a model can produce for conducting a “what-if” analysis. Numerous examples in the literature demonstrate the adoption of MCDA methods and tools in energy-efficient renovation and retrofitting building projects [70,71]. Documentation of existing building renovation projects using various MCDA methods and tools for decision-making is summarised in Table 1. The table covers three aspects of each of the renovation projects: (a) the MCDA method used, (b) the location of the project/case study, and (c) the goal of the project.

In recent years, the Ordinal Priority Approach (OPA) [72] has assisted with group decision-making using preference relations. With OPA, experts, alternatives, and attributes can be weighed and ranked simultaneously using simple steps. OPA is the only MCDA method that allows experts to include the attributes that they believe are relevant in decision-making and disregard the other unimportant attributes [72]. However, Weighted Sum Method (WSM) [73] is a widely used and simply implemented MCDA that may be carried out in a variety of domains, including building renovation [74,75]. WSM refers to decision-making processes and techniques in which each alternative must be given a score

Table 1
A comparison of various MCDA methods and tools used in existing residential building renovation and retrofitting in literature.

Ref.	(a) MCDA method	(b) Location	(c) Goal of the project
[76]	Classic	Europe (Spain)	Energy retrofit solution
[77]	TOPSIS	Europe (Germany)	Renovation solution
[78]	Hybrid (ANP)	Asia (Taiwan)	Revitalization and regeneration
[79]	Fuzzy set	Europe (Lithuania)	Regeneration alternatives
[80]	AHP	Europe (UK)	Green technology assessment
[81]	S-AHP	Asia (South Korea)	Prioritising restoration
[82]	TOPSIS+VIKOR	Europe (Italy)	Seismic Structural retrofitting
[83]	PROMETHEE	Europe (Italy)	Energy retrofit solution
[84]	AHP+VIKOR	Asia (Philippines)	Energy retrofit solution
[70]	TOPSIS	Europe (Spain)	Renovation solution
[75]	WSM	Europe (Sweden)	Renovation solution
[85]	COPRAS	Europe (Lithuania)	Renovation solution
[86]	Classic	Europe (Spain)	Energy retrofit solution
[87]	PROMETHEE	Africa (Algeria)	Renovation solution
[88]	ELECTRE-TRI	Europe (France)	Energy retrofit solution

based on a relevant criterion, with each criterion being weighed according to its significance. WSM is typically used to aggregate attribute values and multiply them by the corresponding weights to get a value.

We use the MCDA approach for decision-makers to prioritise low-carbon building system rejuvenation in Singapore public housing (see Section 3.4). We use a hybrid MCDA method by combining the OPA and WSM. In our proposed building rejuvenation process, experts determine parameters (criteria) and preferences as per OPA. The experts assign weights to parameters, and the aggregate value is classified according to the ranking using WSM. Based on the ranks, buildings with higher values are considered to have more urgency to renovate. This approach highlights the inclusion of experts and stakeholders, to identify, select, and assign weights to the critical parameters in the decision-making process of building renovation.

3. Methodology

We propose a conceptual architecture to develop UDTs for the specific use case of estimating operational GHG emissions of buildings (Section 3.1). We then present a use case for estimating building operational greenhouse gas (GHG) emissions of buildings in Singapore (Section 3.2), based on a developed UDT with an integrated 3D city energy dataset from open data sources representing the built environment and its energy use [60]. Given that historical electricity and cooling demand in Singapore are only available for a few building use types, this dataset is complemented by simulations using a country-scale building energy demand model created on City Energy Analyst (CEA) [44] (Section 3.3). With the energy dataset and GHG emission estimate as a baseline, an analysis—Potential For Intervention (PFI)—is created to help decision-makers prioritise low-carbon building system rejuvenation in Singapore public housing (Section 3.4).

3.1. Conceptual architecture and user-experience of Urban Digital Twin

The proposed conceptual architecture to develop UDTs for estimating the operational GHG emissions of buildings is shown in Fig. 1. The architecture is based on the findings of the literature review [58] and hands-on development of pilot case studies for campus- and city-scale [59,60]. Three structured layers in the proposed architecture illustrate the data flow between physical and digital systems, namely physical, cyber, and cognitive. The physical layer of a smart city consists of many physical components, such as buildings, critical infrastructure, and Building Management Systems (BMS) with actuators and sensors. The physical layer also represents the four life cycle stages of energy use and emission, Product, Construction, Use, and End-of-life. This leads to a greenhouse gas (GHG) inventory that accounts for the release and usage of seven major GHGs: CO_2, CH_4, PFCs, HFCs, SF_6, N_2O, and NF_3. The focus of the research, however, is on the “use” stage of the life cycle, which leads to operational GHG emissions due to energy use in the built environment.

The physical layer information is converted to 3D assets and transmitted to the cyber layer. Within the cyber layer, assets are represented as geo-information models, complete with geometry, coordinates and metadata. Depending on the services required, geo-information models are supported by simulation systems (e.g., building energy demand modelling) and additional climate data. The data storage system supports the User-Experience (UX) platform for presenting processed data to clients. In the proposed architecture, the cognitive layer is made up of the UX platform and its interactive system that supports the user's decision-making process. A feedback loop of interaction between the platform and the user is created by the user applying input scenarios and viewing the corresponding results in charts and decision metrics; this eventually forms the basis for the user's decision-making processes.

Using the data collected (integrated 3D city dataset), operational GHG emissions of buildings are calculated using Equation (1) with an inventory of greenhouse gases. Further, operational GHG emissions specific to MEP equipment used in buildings are calculated using the “basic” methodology provided by Harnot and George [89]. The calculation result is cumulated for all the equipment used in a building. Starting from simple Air Handling Units (AHU) used in residential buildings towards complex MEP equipment used in other typologies (commercial, healthcare, university, etc.).

Simultaneously, the GHG App dashboard along with the UX is set up as a web browser application using *Cesium Ion*, an open cloud platform for hosting 3D geospatial data. *Cesium Ion* tiles massive high-resolution 3D content using 3D Tiles format specification [90] for optimised and rapid streaming over the web. CesiumJS, an open-source JavaScript library is used to programme and customise the GHG App. Highcharts JS, a JavaScript charting library is used to display tailored interactive visualisations in the dashboard [91].

In the GHG App, all features collected with their information (integrated 3D city dataset) are converted and set up to stream on the web using the framework that was tested during our pilot case study [59]. The framework utilises Quantum Geographic Information System (QGIS) software to combine a shapefile with building geometry and attributes related to all buildings available in various data formats. Then Feature Manipulation Engine (FME) software converts the combined shapefile to the required 3D Tiles format.

The GHG App provides two scenes in the dashboard: Scene 1 is dedicated to building operational GHG emissions and energy use data and Scene 2 is used for PFI analysis. In Scene 1, a query system with an input scroll bar of three categories (Planning Area, Built Year, and Building Typology) is created for quick access and navigation to the dataset within the dashboard. Charts are generated with alternative scenarios based on the output of GHG emissions calculation for every building when a user selects the building (using a mouse left-click) on the dashboard (see Fig. 2). The forecasting results of the energy-use trends and corresponding GHG emissions of each building can be visualised for the years 2030 and 2040. In Scene 2, users can choose weights to prioritise various parameters influencing the generation of the PFI map.

3.2. Methodology for calculating operational GHG emissions of buildings

For the development of the use case of operational GHG emissions in buildings, the standard methodology for calculating operational GHG emissions from Mechanical, Electrical, and Plumbing (MEP) equipment used in buildings is studied as part of the research. Consequently, energy modelling results and the 3D dataset are combined to calculate the buildings' operational GHG emissions (O_g) ($kgCO_2e$/year, kg carbon dioxide equivalent per year) using a linear equation:

$$O_g = D_{el} \cdot \sum_i \varepsilon_{el,i} \cdot GWP_i \tag{1}$$

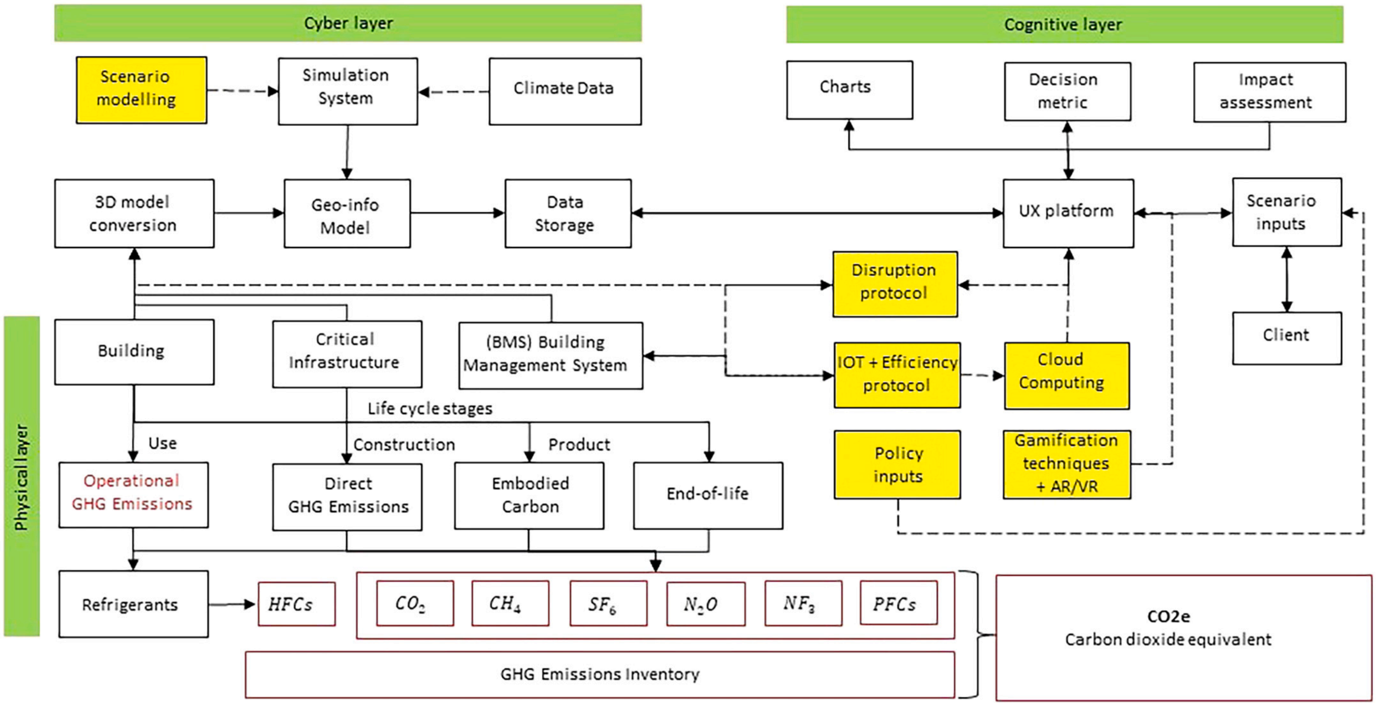

Fig. 1. Conceptual architecture to develop UDTs for a specific use case for estimating buildings' operational GHG emissions. Note: Internet of Things (IoT), VR-Virtual Reality, BMS-Building Management System, AR-augmented reality. Yellow boxes indicate optional technologies specific to six use case groups [58]. (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

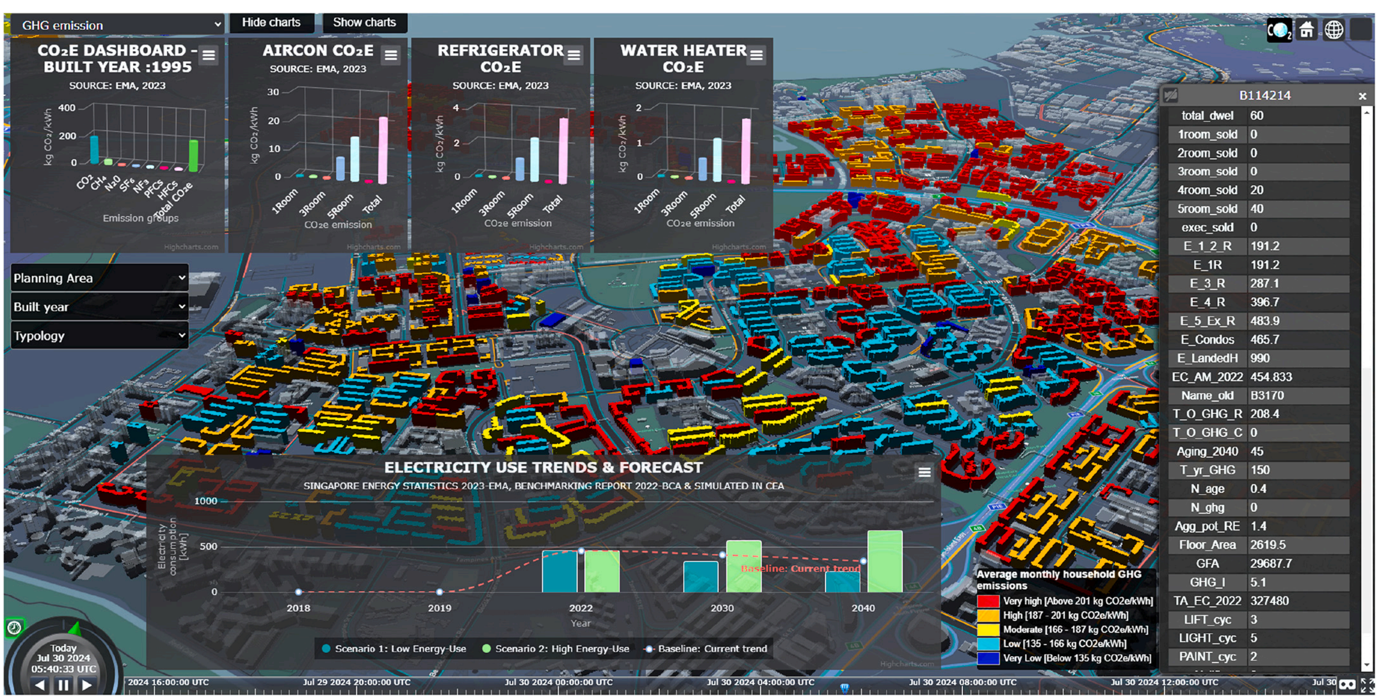

Fig. 2. Dashboard Scene 1 of the GHG App showing operational GHG emissions for Singapore's residential buildings in a heat map (red colour indicates high and dark blue low GHG emissions). The charts at the bottom indicate annual electricity use trends for an individual building. An inventory of the seven major building operational GHG emissions is shown at the top-left corner of the dashboard. Adjacently, building equipment-specific GHG emissions (air conditioning, refrigerator and water heating) in various residential unit types are shown. Meta-data with building information collected can be seen on the right.

where D_{el} = electricity demand per year (kilowatt-hours per year); $\varepsilon_{el,i}$ = electricity grid emission factor for greenhouse gas i; GWP_i = Global Warming Potential for each greenhouse gas i.

The emissions that result from the use of energy to operate mechanical, electrical, and plumbing systems, such as heating, cooling, lighting, ventilation, water supply, and wastewater, are accounted for. Singapore's historical average electricity use is available for residential buildings as provided in the annual Singapore Energy Statistics (SES) reports by the Energy Market Authority (EMA), along with a breakdown per planning area (there are a total of 55 planning areas) and dwelling type (public housing 1-room, 2-room, 3-room, 4-room, 5-room, and executive; landed properties; private apartments and condominiums) [23].

In power generation, the electricity grid emission factor measures the amount of GHG emissions per unit of electricity generated. This factor may vary depending on the source and location of the energy supply and can be obtained from national governments or organisations such as the International Energy Agency (IEA). By calculating the Grid Emission Factor (GEF) for the Operating Margin (OM), we can determine the average amount of CO_2 emitted by the grid-connected power units by each unit of net electricity generation in the system. In Singapore, OM GEF includes electricity generation technologies from primary power producers (such as combined cycle power plants and waste-to-energy plants) as well as auto producers (such as solar energy systems and embedded co-generation plants). A Build Margin (BM) emission factor measures the average of the generation-weighted emission factors across a sample group of power plants *(m)* that were constructed within the given year *(y)* [92]. As a result of the recent construction of new power plants, the BM emission factor in Singapore is lower than the OM emission factor. A slightly higher OM GEF was registered in Singapore in 2022, rising to 0.417 kg CO_2/kWh from 0.409 kg CO_2/kWh in 2021. Diesel consumption increased in 2022 as natural gas markets worldwide tightened, contributing to a higher OM GEF [24]. We refer to the latest yearly publication of the SES report for BM GEF values (0.406 kg CO_2/kWh) to calculate GHG emissions using the linear Equation (1).

Each major greenhouse gas [carbon dioxide (CO_2), methane (CH_4), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), sulfur hexafluoride (SF_6), nitrogen nitrous oxide (N_2O), and nitrogen trifluoride (NF_3)] has a Global Warming Potential (GWP) that compares how much each GHG contributes to global warming over a particular time frame (for example, over a 100-year timeframe). The Intergovernmental Panel on Climate Change (IPCC) reports GWP values for the most common GHGs (CO_2, CH_4, N_2O) [93].

In Singapore, water heaters (11%), refrigerators/freezers (17%), and air conditioners (24%) account for about 52% of a household's total electricity use, according to the weighted energy use profile for all housing types [94]. Therefore, MEP equipment has a major potential in reducing energy use and related GHG emissions. Accordingly, datasets related to MEP equipment used in buildings are required. Specifically, an Environmental Product Declaration (EPD) or use-stage Life Cycle Assessment (LCA) for MEP equipment and a catalogue of MEP equipment currently used in every building in Singapore is required. Using the EPDs and MEP equipment catalogue, a breakdown of building operational GHG emissions from MEP equipment can be estimated [95,96]. However, the datasets mentioned above are not all fully available. There is a lack of a catalogue for MEP equipment used in all the buildings in Singapore, especially for older buildings. EPDs are rarely available for MEP equipment that is installed locally. Further, information on electricity demand and cooling load is openly available for only a limited number of buildings in Singapore.

For the missing EPD and LCA for MEP equipment used locally, the EPD of MEP equipment globally available with comparable specifications is adopted. For instance, Midea published the world's first EPD for split air conditioners using a representative model weighing 37 kg with a service life of 20 years and R32 for refrigerant usage involving electricity use and leakage [97]. The global warming potential (GWP) of the downstream process, which includes the use stage of the air conditioning unit, is 0.0867 kg CO_2e/kWh and a total GWP of 0.0936 kg CO_2e/kWh as per the EPD document. Similarly, EPDs available for refrigerators and water heaters around the globe are used.

In case of a missing EPD, the "basic" calculation methodology explained in standard document TM65 [89] by the Chartered Institution of Building Services Engineers (CIBSE) is used to estimate GHG emissions for each MEP equipment. The GHG emissions (kg CO_2eq/kWh) calculated per equipment are then applied to the entire building depending on the total number of MEP equipment used to find the total building operational GHG emissions. For example, a typical 4-room public housing unit in Singapore may have one refrigerator, one or two water heaters depending on the number of bathrooms, and three to four air conditioning units. Predicting the total number of equipment used within a typical residential unit is relatively easier than for complex typologies such as mixed-use, commercial, and industrial typologies. Hence, the study of MEP equipment-based emissions and the development of archetypes for various typologies beyond residential buildings are still in progress.

Historical electricity use and cooling load datasets for buildings in Singapore are further used to create future scenarios of high and low energy use (with a breakdown of energy use of air conditioners, refrigerators/freezers, and water heaters) and to calculate respective operational GHG emissions in buildings. The missing energy-use data for buildings and forecasts are simulated in City Energy Analyst (CEA) [44], as explained in the following section.

The initial pilot case study and UDT development were for the National University of Singapore university campus with 300 buildings with a COVID-19 scenario case study [59]. An integrated 3D city dataset can be accessed by users within the dashboard with visualisation and query options. Based on the pilot study, UX and cognitive dashboard development were improved with data acquisition and updating from open access reliable data available on government websites. This process involved modelling and data classification of 119k features representing the built environment of Singapore. As a tangible output, the research contributes towards creating a visualisation and query dashboard as a web browser application for stakeholders interested in the decarbonisation of cities through intuitive quantitative operative GHG emission. This idea can be extended and scaled up to show other cities in various countries in the world as a database and be used as a tool to track GHG emission goals set by the United Nations Framework Convention on Climate Change (UNFCCC).

3.3. Simulating energy demand in case of missing energy use data and generating alternative scenario outputs using a forecasting method

In order to estimate the GHG emissions of buildings and typologies not included in the open dataset, a country-scale building energy demand model is created on the open-source tool City Energy Analyst (CEA) [44]. The model primarily comprises building geometries, assigned typologies for each building, and construction standards. This model uses the building footprints, heights, and numbers of floors taken directly from the 3D city dataset and assigns building typologies and construction standards based on information available in OpenStreetMap (OSM) [98] and the Singapore Master Plan 2019 Land Use layer available on Singapore's open data portal [99].

In the first step, the building geometries obtained from the 3D city dataset are checked for feasibility and adjusted where necessary. Floor-to-floor heights larger than 10 m or lower than 1 m are assumed to be due to errors in the data, and therefore for such buildings, the number of floors is adjusted based on an assumed typical floor-to-floor height. This typical building's floor-to-floor height is assumed to be 4 m based on the median of all floor-to-floor heights between 1 and 10 m encountered in the original dataset. This value is also used to estimate the number of floors for buildings for which only the building height was available and could be calculated. Finally, CEA cannot process buildings with heights above ground less than 1 m, therefore as a simplifying assumption, all such buildings are assigned a minimum height of 3 m.

Each building is subsequently assigned one of the typologies available in CEA, as summarised in Table 2. Since OSM data is building-specific while land use data corresponds to entire districts, buildings are first assigned their typology based on the category assigned in OSM, if any. Where buildings have no assigned category on OSM, or if these are not clear enough, they are assigned a typology based on the land use type for the area in which they are located. Given the limited number of typologies available in CEA, some of the typologies need to be simplified. For example, train stations are assigned the use type *RETAIL* for simplicity. All unconditioned building use types are assigned the *PARKING* use type in order to ensure they are not assumed to be conditioned by CEA. Most buildings are assumed to have a single-use type

Table 2
Building typologies and construction standards assigned for each building in the City Energy Analyst (CEA) model by OpenStreetMap (OSM) category and land use type. (*) For all buildings with *STANDARD3*, if the OSM roof material was specified as "grass", *STANDARD5* was used instead.

CEA Typology	OSM category	Land use type	CEA standard
MULTI_RES	'residential', 'apartments', 'condominium', 'dormitory'	'Residential'	*STANDARD1*
MULTI_RES and *OFFICE*	—	'Commercial & residential', 'Residential/Institution', 'White'	*STANDARD1*
MULTI_RES and *RETAIL*	—	'Residential with commercial at 1st storey'	*STANDARD1*
SINGLE_RES	'detached', 'house', 'semidetached_house', 'semi_detached'	—	*STANDARD2*
OFFICE	'office', 'civic', 'government', 'commercial'	'Business park', 'Civic & community institution', 'Commercial', 'Commercial/Institution'	*STANDARD3*(*)
RETAIL	'retail', 'shop', 'train_station', 'yes;retail'	'Light Rapid Transit', 'Mass Rapid Transit'	*STANDARD3*(*)
INDUSTRIAL	'industrial', 'manufacture'	'Business 1', 'Business 2'	*STANDARD3*(*)
GYM	'sports_centre', 'sports_hall', 'swimming_pool_changing_room', 'grandstand', 'stadium'	'Sports & recreation'	*STANDARD3*(*)
HOSPITAL	'medical', 'hospital'	'Health & medical care'	*STANDARD3*(*)
MUSEUM	'museum', 'chapel', 'church', 'mosque', 'religious', 'shrine', 'temple'	'Place of worship'	*STANDARD3*(*)
SCHOOL	'school', 'kindergarten', 'CET_Campus_East'	—	*STANDARD3*(*)
UNIVERSITY	'university', 'college'	'Educational institution'	*STANDARD3*(*)
HOTEL	'hotel'	—	*STANDARD3*(*)
FOODSTORE	'supermarket'	—	*STANDARD3*(*)
PARKING	'hall', 'multi-purpose_hall', 'bridge', 'parking', 'carport', 'IMM', 'stable', 'roof', 'shed', 'hut', 'pavilion', 'gazebo', 'warehouse', 'greenhouse', 'multi-purpose_stage', 'transportation', 'garage', 'service', 'toilets', 'farm_auxiliary', 'hangar', 'Security_Post', 'parlour', 'construction', 'fire_station'	'Agriculture', 'Cemetery', 'Open space', 'Park', 'Port/Airport', 'Reserve site', 'Road', 'Special use', 'Transport facilities', 'Utility', 'Waterbody'	*STANDARD3*(*)

Table 3
Building system operation parameters and internal gains by building typology according to the CEA database [44].

CEA Typology	Setpoint temperature [°C]	Ventilation rate [l/s/p]	Occupant density [m^2/p]	Occupant gains		Electricity demand			Hot water demand [l/d/p]
				Sensible [W/p]	Latent [g/h/p]	Appliances [W/m^2]	Lighting [W/m^2]	Processes [W/m^2]	
MULTI_RES	28	10	35	70	80	2	5	0	40
SINGLE_RES	28	10	60	70	80	2	5	0	40
OFFICE	24	10	10	70	80	11	10	0	0
RETAIL	24	8	6	70	90	2	33.3	0	2
INDUSTRIAL	24	31	13	90	170	20	14.7	16.5	10
GYM	24	10	9	110	255	2	9.9	0	40
HOSPITAL	24	10	19	70	80	8	11	0	0
MUSEUM	24	10	10	70	80	7	10.8	0	0
SCHOOL	24	8	4	70	80	16	12	0	0
UNIVERSITY	24	10	19	70	80	16	12	0	0
HOTEL	24	10	23	70	80	4.3	3.1	0	40
FOODSTORE	24	10	0	70	80	5	9.3	0	2
PARKING	–	0	0	0	0	0	5	0	0

for simplicity, except for buildings with no OSM category located in specific land use areas, such as "Commercial & residential" and "Residential with commercial at 1st storey". Building heights, number of floors, and typologies occasionally need to be corrected manually where outliers or unclear category assignments in OSM are discovered. The building operation parameters (setpoints, internal gains, electricity demands) associated with each of the typologies used according to the CEA database are summarised in Table 3.

Finally, in order to assign construction materials and envelope properties, CEA requires a construction standard to be selected. The number of standards available is limited, as shown in Table 4. Again, for simplicity and due to the limited amount of information available, each typology presented in Table 2 is assigned a single CEA construction standard. Since *STANDARD1* is intended to be typical for public housing, which is the predominant type of residential building in Singapore, all multi-family residential buildings are assigned that standard. *STANDARD2* is defined as being typical of private housing in Singapore, therefore all single-family units are assigned that standard. All other building use types are assigned one of the commercial construction standards in CEA. For buildings that are tagged in OSM as having green roofs, (i.e., roof material "grass"), *STANDARD5* is chosen. For all other buildings *STANDARD3* is used.

The remaining inputs for the CEA model include typical inputs in building energy simulations, such as occupancy patterns, building operation parameters, internal gains, and electricity demands. Since this information is typically not available at an urban scale, CEA includes an archetypes database to assign these parameters based on the building typology, and construction standard. Using the geometry, typology, and construction standards discussed above, along with the archetype database, a country-scale CEA model for Singapore is created.

Each run of the building energy demand model involves a yearly solar irradiation simulation followed by a building energy demand simulation [100]. At country-scale, these come at significant computational expense, and therefore two methods are pursued to make the simulations feasible. First, in order to reduce the computational time and parallelise the simulations, the country-scale model is split into smaller projects based on the Singapore Master Plan 2019 Subzone Boundary [101]. Thus, instead of running all of the nearly 120,000 buildings all at once, the simulations are split into batches of less than 3,000 buildings per simulation. To further reduce computational time, the simulations are executed by onboarding a processor onto ASPIRE2A, an AMD (Advanced Micro Devices) based Cray EX supercomputer at the National Supercomputing Centre (NSCC), Singapore. The results from the energy modelling and 3D dataset are combined to calculate buildings' operational GHG emissions using Equation (1).

Table 4
Construction standards available in CEA [44] and their corresponding envelope properties and cooling system type.

CEA Standard	Description	Air tightness [ach]	U-values [W/m^2·K]				Window-to-wall ratio	Cooling system
			Roof	Wall	Floor	Window		
STANDARD1	Residential, reduced conditioned areas	0.32	0.6	0.8	2.9	5.4	0.29	mini-split AC (6/15)
STANDARD2	Residential, increased conditioned areas	0.32	0.6	0.8	2.9	5.4	0.29	mini-split AC (6/15)
STANDARD3	Commercial (default)	0.22	0.6	3.2	2.9	2.2	0.59	central AC (6/15)
STANDARD4	Commercial (low window-to-wall ratio)	0.22	0.6	3.2	2.9	2.2	0.29	central AC (6/15)
STANDARD5	Commercial (green roofs)	0.22	0.15	3.2	2.9	2.2	0.59	central AC (6/15)

A forecasting method is proposed to estimate energy use and GHG emissions along with alternative scenarios for the years 2030 and 2040 (leading to a net zero emissions target for 2050). For each future scenario, a new energy demand simulation is run with updated weather files based on future weather projections using the Coupled Model Intercomparison Project Phase 6 (CMIP6) data. Following Mosteiro-Romero et al. [53], we use CMIP6 model AWI-CM-1-1-MR and scenario SSP585, which represents the high end of the range of future pathways. In addition to the effects of climate change, scenarios are defined to assess how future developments might support achieving future emission targets. These include varying building operation schedules and system parameters to assess the effect of various country-scale policies. These future scenarios can also be simulated using the country-scale building energy demand model.

3.4. Potential for intervention (PFI) analysis

The Potential for Intervention (PFI) map is created using the MCDA method. A PFI map aims to assist decision-makers in prioritising the rejuvenation of low-carbon building systems in Singapore's public housing. For a future scenario in the year 2040, we generate the PFI map using MCDA for existing residential buildings to demonstrate the decision-making scenarios associated with building system rejuvenation. Rejuvenation involves renovating or retrofitting, i.e., replacing old and inefficient building systems with more energy-efficient and low-carbon alternatives. The resulting PFI heat map shows the buildings that need urgent rejuvenation based on parameters that influence the decision.

The PFI map adopts the Ordinal Priority Approach (OPA) from MCDA for choosing influential parameters. Based on OPA, experts provided the parameters they deemed relevant to creating a multi-criteria decision analysis and a resulting PFI value for each residential building. Five parameters are selected based on the feedback received from experts who analyse future ageing infrastructure in Singapore. Subsequently, weights are assigned to each selected parameter based on their significance as decided by the expert user. The Weighted Sum Method (WSM) from MCDA is used to individually multiply parameters by the corresponding weights and aggregate five parameter values to get the PFI values for each building.

The parameters selected to create PFI values are: (1) Building age, (2) Greenhouse gas (GHG) emissions, (3) Replacement cycles for lifts, (4) Replacement cycles for lighting equipment, and (5) Building wall painting cycles. These parameters have varying scales and hence a normalisation method of applying a notionally common scale to values measured on different scales using a function is required to aggregate parameters [102]. Logistic sigmoid functions are used to convert each parameter to a 0 to 1 value before aggregating, and the midpoint (0.5) for each parameter is the threshold beyond which there is a need for an intervention from the decision maker (see Fig. 3). For instance, the Building age parameter is assigned a threshold of 50 years, beyond which maintenance is required. Similarly, public housing has certain thresholds for replacement cycles of building equipment used (such as lifts and common area lighting). After the normalisation step, each parameter is aggregated based on WSM to find the Potential For Intervention (higher PFI values indicate a higher potential for renovating the building). A ranking is determined by five categories ("Very High", "High", "Moderate", "Low", "Very Low") on an ordinal scale using quantiles. The result of the aggregate potential for intervention with each parameter weighted equally (Case 1) is visualised in the dashboard as a PFI heat map (see Fig. 4). Additionally, the dashboard provides users with an option to change the weightage of the parameters based on their priority and, then, automatically updates the PFI map with the newly assigned weights. From the PFI heat map, users can examine buildings with higher PFI values and rankings to plan an intervention for building system renovation.

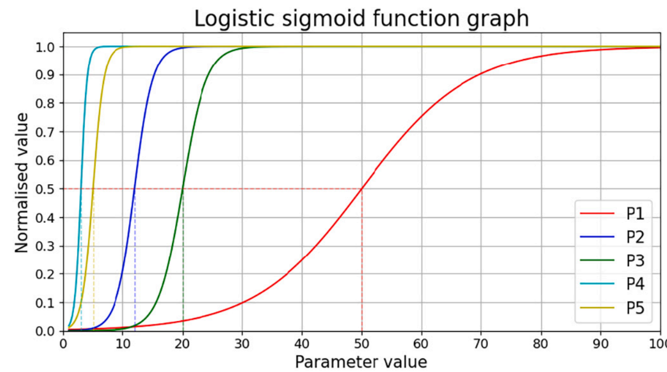

Fig. 3. Logistic sigmoid function graph for the five selected parameters showing the transformation of each parameter value (x-axis) into the range of 0-1 (y-axis) using Equation (2). The dotted lines represent each individual parameter's infliction point.

Table 5
Variables used in the sigmoid function (Equation (2)) for normalisation of five different parameters.

Parameters *Pn*	*a* (mid-point)	*b*
P1 Building Age	50	9
P2 GHG emissions intensity	12	1.5
P3 Lift replacement cycle	20	2
P4 Lighting replacement cycle	3	0.5
P5 Building painting cycle	5	0.9

3.4.1. Parameters for the PFI analysis

The parameters that most influence the rejuvenation processes are considered for the PFI analysis. Experts establish these parameters based on their current work on rejuvenating public housing. The following are the PFI analysis parameters, their corresponding thresholds set by experts and respective logistic sigmoid functions used to normalise the parameter values based on the respective thresholds (mid-point-0.5). Equation (2) is used to normalise parameters Pn based on the variables a and b shown in Table 5.

$$f(Pn) = \frac{1}{1 + \exp\left(\frac{a - Pn}{b}\right)} \tag{2}$$

Building Age *(P1)*:

The Voluntary Early Redevelopment Scheme (VERS) and Selective En bloc Redevelopment Scheme (SERS) both aim to renew Singapore's older public housing estates. Both schemes aim to revitalise estates

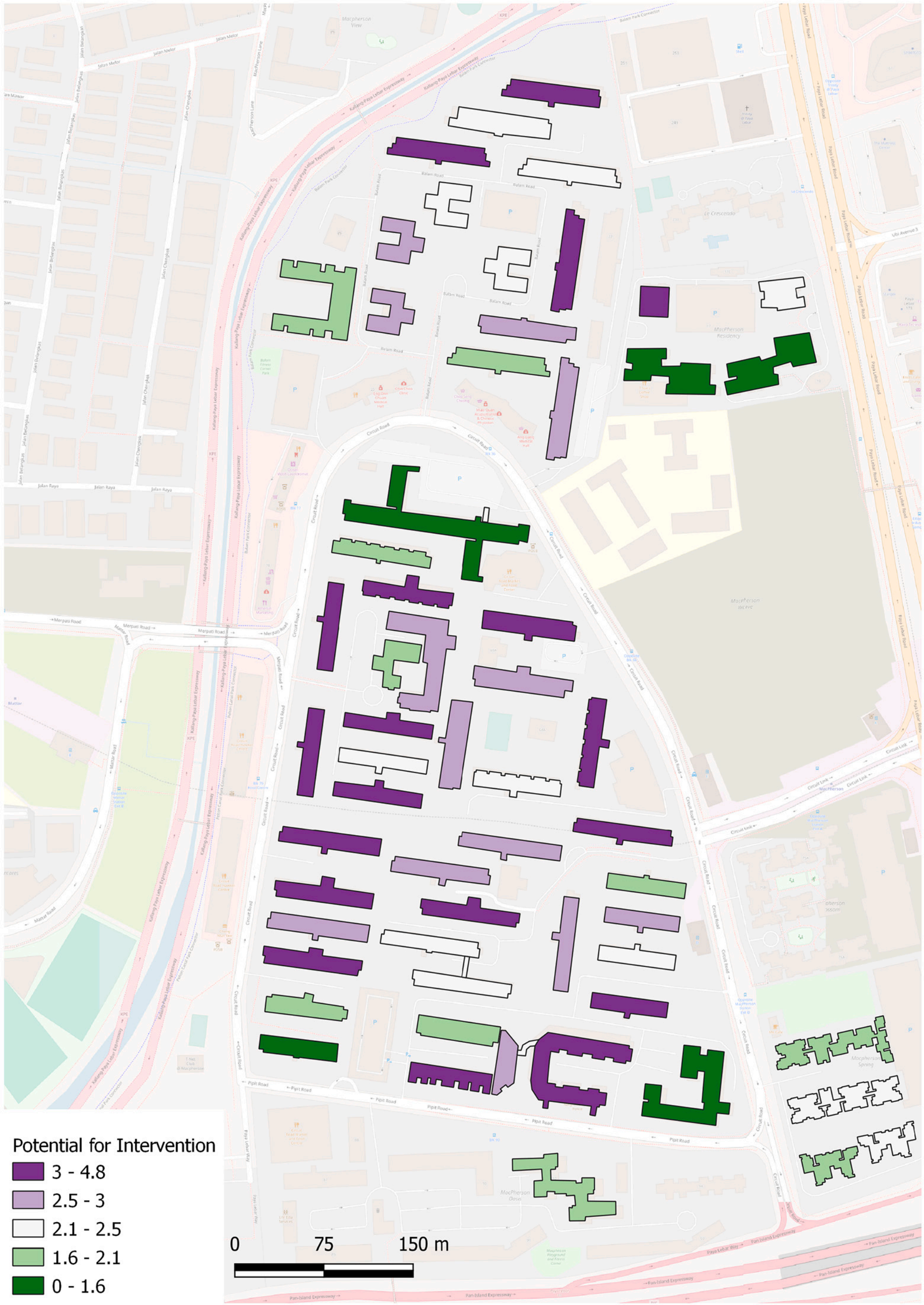

Fig. 4. A sample (Case 1) heat map of Aggregate Potential for Intervention analysis results for the 2040 scenario for the residential building stock in Singapore. Purple-coloured buildings indicate very high PFI values and dark green buildings suggest low PFI values.

by taking back flats before their leases expire and redeveloping them. Precincts over the age of 70 will be offered the VERS voluntary scheme. In SERS, selective land with high redevelopment potential is utilised for redevelopment. The increasing stock of ageing infrastructure (above 50 years old) and resource constraints in Singapore before 2040 raise concerns. Hence, we set the Building Age parameter *(P1)* to the inflection point of 50 years old in 2040, beyond 50 years rejuvenation interventions will be considered for the building. The Building Age parameter can further be considered to support existing public housing upgrading initiatives such as the Home Improvement Programme (HIP) [103]. Accordingly, the logistic sigmoid function (Equation (2)) transforms each building's age *(P1)* into a value between 0 and 1. For instance, buildings that turn 50 years old in 2040 are assigned a 0.5 value, and the normalised value increases towards 1 with age (see P1 in Fig. 3).

GHG emissions intensity *(P2)*:

To compare buildings, the intensity of GHG emissions should be considered. GHG emission intensity is calculated by dividing a building's total GHG emissions in a year by its total gross floor area (GFA). This provides a better comparison between buildings, as otherwise, buildings with larger footprints would always have higher GHG values. Buildings can then be ranked based on emission intensity per square meter of building floor area (Section 4). However, there is no standard for

Table 6
Comparison of three cases with varied input parameter weights. The re-scaled weights for case 2 and 3 are shown in the brackets.

Parameters	Case 1	Case 2	Case 3
P1 Building Age	1	2 (1.429)	1 (0.75)
P2 GHG emissions intensity	1	2 (1.429)	1 (0.75)
P3 Lift replacement cycle	1	1 (0.714)	2 (1.25)
P4 Lighting replacement cycle	1	1 (0.714)	2 (1.25)
P5 Building painting cycle	1	1 (0.714)	2 (1.25)

restricting operational GHG emissions in the region's building sector. Therefore, we set an infliction point at 12 $kgCO_2e/m^2$.yr based on studies available on GHG emission intensity of high residential buildings in Asia [95,96]. Accordingly, the logistic sigmoid function (Equation (2)) transforms a building's GHG emission intensity *(P2)* into a value between 0 and 1. For instance, Buildings with GHG emission intensity of 12 $kgCO_2e/m^2$.yr are assigned a 0.5 value, and the normalised value increases towards 1 with GHG emission intensity value (see P2 in Fig. 3).

Lift replacement cycle *(P3)*:

The Housing Development Board (HDB) of Singapore implements the Lift Upgrading Programme (LUP) which tends to occur in a time frame of 10–30 years for the building lift renovation cycle [104]. We do not have access to real lift age or replacement cycle information. Therefore, we have created simulated data by randomly assigning all public residential buildings a value between 1–30 years as the lift age. We aim to set the lift replacement cycle parameter at the inflection point of 20 years old by 2040. This means that beyond twenty years in 2040, the elevators in the building will require rejuvenation interventions. Accordingly, the logistic sigmoid function (Equation (2)) transforms the lift age *(P3)* into a value between 0 and 1. For instance, lifts that turn twenty years old are assigned a 0.5 value, and the normalised value increases towards 1 with age (see P3 in Fig. 3).

Lighting replacement cycle *(P4)*:

Public residential buildings in Singapore undergo regular maintenance by HDB along with the Town Council [105], which includes retrofitting common area lighting. The HDB Green Towns Programme [106] has been looking for innovative ways to reduce electricity use in common areas of public housing estates. Smart lighting is one of the solutions implemented with motion sensors and analytic capabilities. This technology reduces 60% of energy used for lighting by automatically adjusting LED lights' brightness based on detected motion compared to conventional LED lighting. HDB works with Town Councils to install smart lighting in all common areas of buildings built before 2014 when their existing LED lights are due for replacement (3–5 year cycle). We aim to set the lighting replacement cycle parameter at three years by 2040 so that common area lights will require rejuvenation interventions beyond that time. Accordingly, the logistic sigmoid function (Equation (2)) transforms the age of the lighting fixtures in the common areas *(P4)* into a value between 0 and 1. For instance, lights that turn three years old are assigned a 0.5 value, and the normalised value increases towards 1 with age (see P4 in Fig. 3).

Building painting cycle *(P5)*:

Regular maintenance by the public housing town council is conducted with regular block-painting exercises at 5–7-year intervals. We do not have access to real building painting cycle information. Therefore, we have created simulated data by randomly assigning all public residential buildings a value between 1–7 as their years since the last painting cycle. We aim to set the building painting cycle parameter at the inflection point of 5 years by 2040 so that rejuvenation interventions are required after that time for the building facade and common areas. The building painting cycle parameter can further be considered to support existing initiatives such as the periodic façade inspection by the Building and Construction Authority (BCA) of Singapore [107]. Accordingly, the logistic sigmoid function (Equation (2)) transforms the time elapsed since a building was last painted *(P5)* into a value between 0 and 1. For instance, buildings that have not been painted for five years are assigned a 0.5 value, and the normalised value increases towards 1 with age (see P5 in Fig. 3).

3.4.2. Varied input parameter weights in three cases

Three cases are introduced to demonstrate how varied user priority or input parameter weights (see Table 6) are aggregated, categorised using quantiles, ranked and visualised in the dashboard. In the dashboard, each parameter can be weighted between 0 and 5, with 5 being the highest priority. If a parameter is set to 0, that specific parameter will not be considered for the aggregate PFI value. Section 4 further analyses and compares the results of PFI analysis through three cases with varied input weights (Table 6). In Case 1, all parameters are given equal weights, considering each parameter as important. Case 1 is set as the default input parameter weight in the dashboard. In Case 2, more importance is placed on the Building age (P1) and GHG emissions intensity (P2) parameters, evaluating overall building performance by highlighting ageing infrastructure and emissions. In Case 3, the lift replacement (P3), lighting replacement (P4) and building painting (P5) cycles are given more weight than the other two parameters, evaluating the overall building maintenance. Cases 2 and 3 carry more weight compared to the default Case 1. To facilitate comparison, all weights in cases 2 and 3 are re-scaled to reach a maximum total parameter weight of 5.

4. Results and discussion

In this section, the outcomes of the estimation of total operational GHG emissions for buildings and the comparison with the intensity of operational GHG emissions are presented and analysed. Subsequently, PFI results for three different cases with varying parameter weights are generated. Then, buildings in each case are ranked into five categories based on quantiles. Parameter sensitivity is shown with PFI and individual parameter values. We discuss our pilot studies, analyses, and the latest results that are demonstrated using an open-access web browser application dashboard—*GHG App*. The final part of our discussion focuses on our use case to renovate existing ageing residential buildings in Singapore using a low-carbon renovation concept, as well as how such tool demonstrations and assessments can help cities reduce carbon emissions and implement related policies.

4.1. Estimation of operational GHG emission results

Based on the average electricity use of units, the total building operational GHG emissions are estimated for the entire building. Additionally, MEP equipment-related (air conditioner, refrigerator and water heater) GHG emissions for a building are part of the dashboard. A comparison of total building operational GHG emissions and estimated GHG emission intensity along with building height is shown in Fig. 5. Dwelling types and built years of buildings are used to categorise the buildings and find any emissions patterns. Total GHG emissions have a direct correlation with building height and electricity use. On the other hand, GHG emissions intensity does not increase with building volume and can, therefore, be compared from building to building.

The buildings with predominantly 4-room and 3-room dwelling types have higher GHG emissions per year in the sample (6785 buildings), as shown in Fig. 5(a). This is because they tend to have higher building electricity use, with a larger number of these apartments and a higher rate of air conditioning units within each apartment. 5-room or Executive types are the largest dwelling types with the highest electricity use per apartment; however, they are not as densely stacked together compared to 4-room and 3-room dwelling types. Fig. 5(c) indicates that newer buildings built after 2010 tend to be taller and have predominantly 4-room, 3-room, and 5-room dwelling types.

4.2. PFI results

A histogram is shown for three different cases with varying parameter weights (see Fig. 6). Case 2 (initial weight 7) and Case 3 (initial

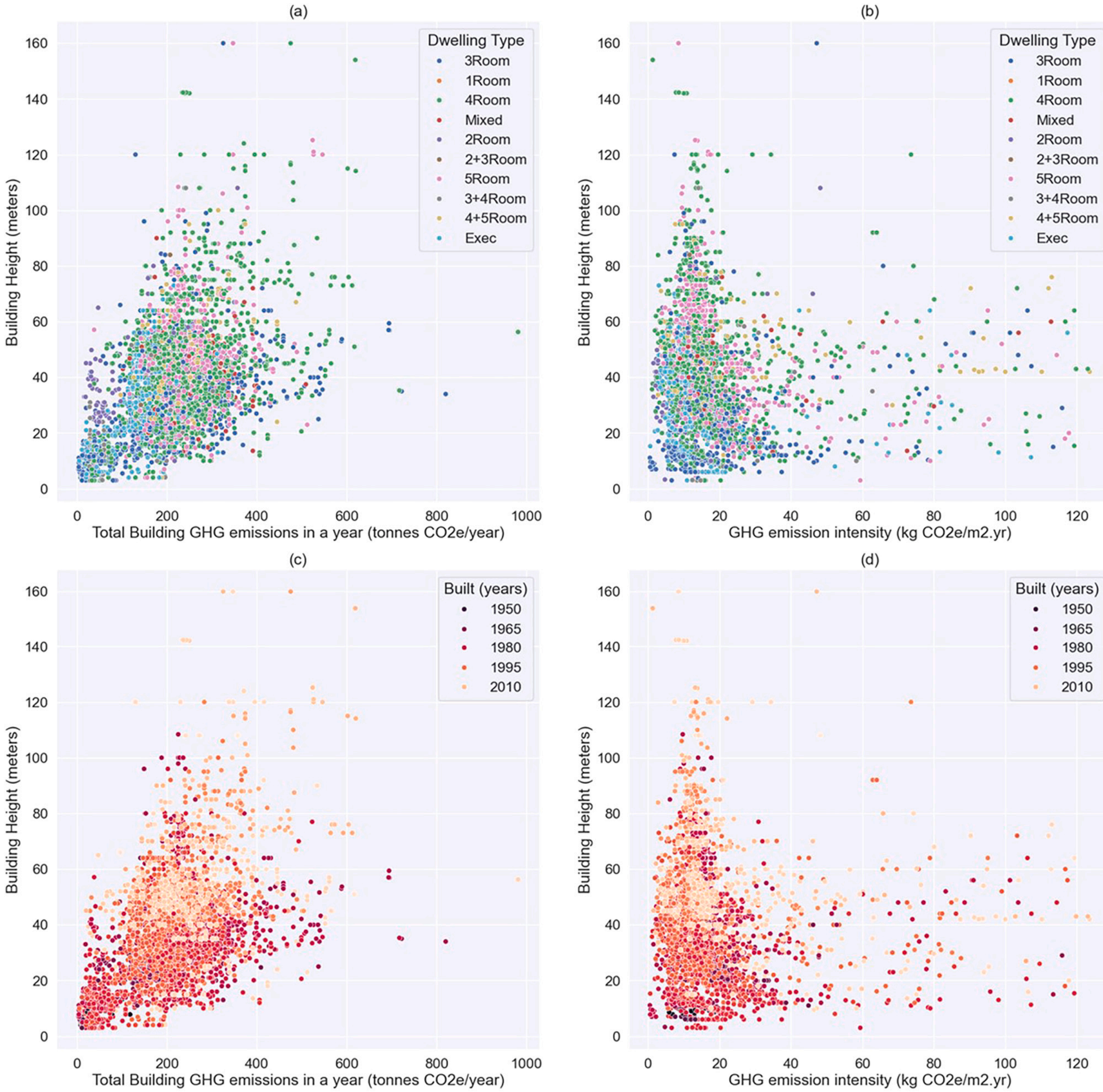

Fig. 5. Comparison of residential buildings' total GHG emissions for the year 2022 (x-axis) and GHG emission intensity (x-axis) respectively with building height (y-axis), with buildings categorised based on dwelling types (a, b) and built year (c, d).

weight 8) have weights re-scaled to match Case 1 (weight 5). The rescaled weights for Case 2 and Case 3 are shown in brackets in Table 6. After rescaling, all cases have an added weight of 5 and hence can be compared. Ranks based on quantiles classify buildings into five categories. The probability distributions are divided into intervals of equal probability (20%) by cut points in the PFI range for each case. Accordingly, buildings with PFI values above quantile Q4 (i.e. 80%) are categorised as "Very High", values between Q4 and Q3 (60%) as "High", between Q3 and Q2 (40%) as "Moderate", between Q2 and Q1 (20%) as "Low", and below Q1 as "Very Low".

Fig. 6 shows the PFI value quantiles for Case 2 are higher as compared to Cases 1 and 3. Case 2 has two parameters (P1 and P2) that are assigned high priority (or weight), while Case 3 has three parameters (P3, P4 and P5) with higher priority, and Case 1 has equal parameter weights. Higher PFI value quantiles in Case 2 mean that there are a large number of buildings that are older (above 50 years) and have high GHG emission intensity (above 12 $kgCO_2e/m^2$.yr).

In general, when users give various weights to each parameter, PFI and respective quantile values will shift. The parameter sensitivity is illustrated with plots of the PFI and the individual parameter values (see Fig. 7). The GHG App computes quantiles for PFI values each time users change parameter weights and respectively ranks buildings (Very High to Very Low) based on the quantiles (see Fig. 8). In the PFI analysis, only the public areas of the residential buildings are considered for intervention and the energy use of the apartments remains unchanged.

4.3. Discussion

With the methodology introduced in Section 3, we developed an integrated 3D dataset for Singapore with more than 119k features representing its buildings and infrastructure. The dataset is further classified based on planning area, building year and building typology. Moreover, such 3D datasets created particularly for energy systems can further be used to train machine learning models and study city energy use

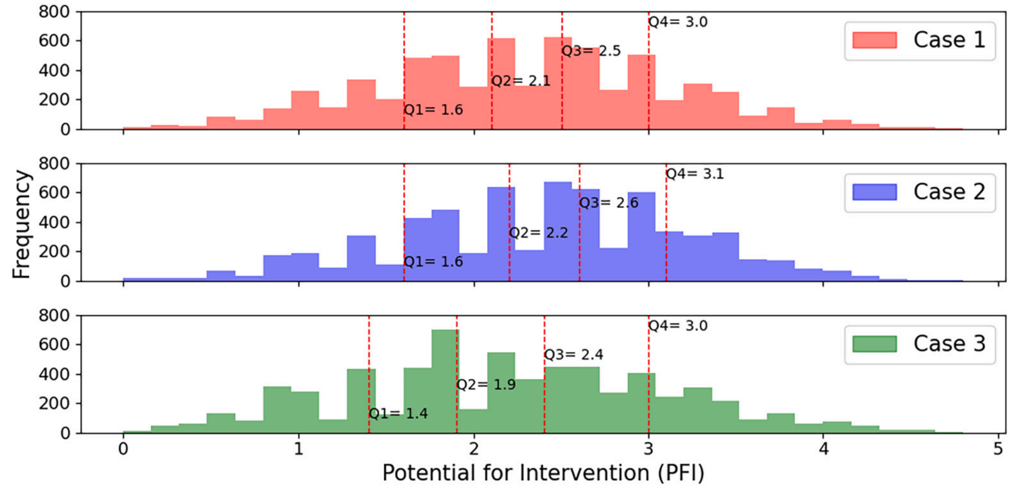

Fig. 6. Graph showing PFI results (x-axis) of three sample cases with varied input parameter weights and frequency plotted on the y-axis. The quantiles—Q1, Q2, Q3, and Q4 are indicated in dotted red line for each sample case.

patterns. For instance, yearly building energy use intensities can help forecast energy demands for assessing net-zero energy goals for cities. Furthermore, as explained, additional datasets related to the mobility sector (car park occupancy in this case) can help define scenarios regarding future trends in electricity demand, assess the impact on existing infrastructure, and prepare for potential future shocks to further enhance its resilience. User Experience (UX) with real-time and historical data interaction is what sets UDTs apart from other visualisation platforms. Beyond visualisation, they offer the latest empirical data to support stakeholders in the decision-making process and generate what-if scenarios for further analysis. The use case presented here provides scenarios that a user can explore and make decisions based on the displayed analysis results in the dashboard.

UDT use case classifications are siloed inside sectors. However, use cases found during the literature review demonstrated multi-scale and interdisciplinary approaches. Most UDTs are developed within organisations and lack access towards further research and testing. Use cases are found to be often classified based on the technologies used, the level of detail of the model, their life cycle phases, and the sector to which they are confined. Use cases dedicated to GHG emission mitigation and related policy development or action are rare and need to be explored.

Operational GHG emissions of buildings are highly dependent on MEP equipment usage, especially in countries with tropical weather conditions such as Singapore. Life cycle assessment (LCA) of MEP equipment is a dedicated method to calculate GHG emissions. Particularly, the use stage of the LCA method for MEP equipment gives an estimate of operational GHG emissions for buildings. A global initiative of the International Environmental Product Declarations (EPD) offers transparent, precise, and comparable information about the environmental effects of goods and services throughout their entire life cycles. EPDs show how committed a manufacturer is to determining, reducing, and disclosing the environmental impact of its products and services. However, EPDs are not easily available for MEP equipment (for instance, split-type air conditioners). In the case of non-availability of EPDs, CIBSE TM65: [2021] provides two ("basic-level" and "mid-level") calculation methods for LCA of MEP equipment used in buildings. We use the "basic-level" calculation methodology for estimating the operational GHG emissions from the use stage (B1 to B7), as EPD is not accessible or not available for the majority of the MEP equipment used in historic buildings. Assuming more information on MEP equipment is publicly available in the future, the calculations will be updated from "basic" to "mid-level" or EPD.

Developing UDTs requires authoritative 3D datasets, which are not easily accessible in many countries, including Singapore. Although bottom-up approaches can help, raw open data collected from non-regulated sources requires further processing and validation. However, such data can still be useful for testing, research, and demonstration. By collecting and processing data from open-to-public sources, an integrated city energy dataset can be created to build UDTs.

Two pilot case studies [59,60] have shown that UDTs can be created without an authoritative 3D dataset to start with. Furthermore, the literature review [58] revealed that synthetic and simulated data can replace authoritative 3D datasets. However, synthetic and simulated data are mainly used in scenario modelling, participatory planning, and policy development use cases. On the other hand, use cases such as operational optimisation, emergency planning, and district-/city-level forecasting rely on actual historical measured data. Evaluating the reliability of synthetic or simulated data used is a challenging task and will be addressed in future research.

A typical approach used in developing organisational UDTs is the top-down approach, which starts with accessible, measured, and highly reliable data. However, there is a need for workflows that demonstrate a low-cost, sophisticated infrastructure and architecture built using an open data-based bottom-up approach. These approaches should replicate the traditional cyber-physical system layers in their architecture while offering a clear distribution of components across the physical, digital, and cognitive layers. Our proposed conceptual architecture represents each component in the layers defined by traditional CPS ideas.

There are only a limited number of examples of how UDTs can be used for smart city energy management purposes. Therefore, there is a need for more demonstrations to be built in this area. On-demand extraction of 3D city features in a web browser, using the 3D Tiles format and *Cesium Ion*, significantly enhances the performance of applications compared to explicit data formats, which can cause slow load times. By creating a robust user-experience dashboard that includes input scenarios and visualisation tools to analyse energy-use data based on historical behavioural patterns, there is great potential for decision-makers to use UDTs to support decarbonisation initiatives in cities.

Our study documents MCDA methods used in decision-making related to building renovation in the literature and contributes a novel UDT approach combined with a hybrid MCDA method for renovation strategies to the discussion. Our study illustrates the benefit of UDTs as a decision-making tool to guide building renovation strategies aligned with ongoing efforts within IEA EBC Annex 89 [108].

5. Conclusion

The *GHG App* and PFI analysis can assist decision-makers in prioritising and planning the renovation of low-carbon building systems. The purpose of this research is to increase stakeholder awareness by provid-

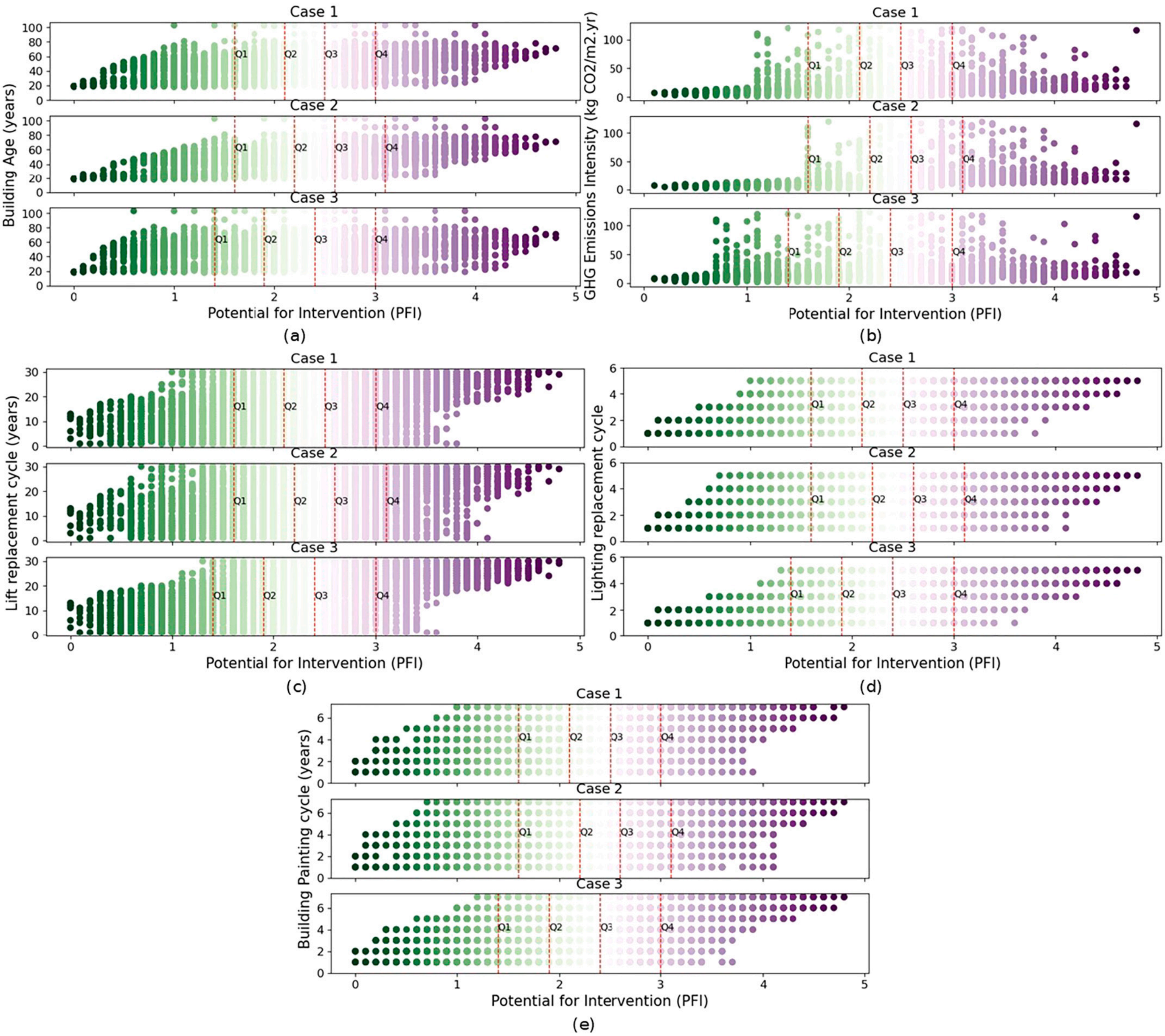

Fig. 7. PFI results for three sample weightage cases for each of the selected parameters: (a) P1 - Building Age in years, (b) P2 - GHG emission intensity in kg CO_2/m^2.yr, (c) P3 - Lift replacement cycle in years, (d) P4 - Lighting replacement cycle in years, and (e) P5 - Building painting cycle in years. The PFI values for buildings are indicated in a colour gradient—dark green (very low PFI value) to purple (very high) for each case. The quantiles—Q1 (20%), Q2 (40%), Q3 (60%), and Q4 (80%)—are indicated by the dotted red line based on the PFI value distribution in every case.

ing: (i) a theoretical investigation (methodology for estimating building operational GHG emissions, scenario simulation, and PFI analysis) and (ii) a practical tool (open access use case demonstration) so that more environmental considerations can be taken into account when building rejuvenation is done. The built environment sector does not currently have a cap on the amount of greenhouse gases it emits in many parts of the world. Our research can help establish standards for accounting for operational GHG emissions, setting emission limits, and assessing decarbonisation plans in the built environment sector.

CRediT authorship contribution statement

Pradeep Alva: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Martín Mosteiro-Romero:** Writing – review & editing, Resources, Investigation, Data curation. **Clayton Miller:** Writing – review & editing, Supervision. **Rudi Stouffs:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Rudi Stouffs reports financial support was provided by National Research Foundation Singapore. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://ghg.app.frs.ethz.ch/ (open-access GHG App)

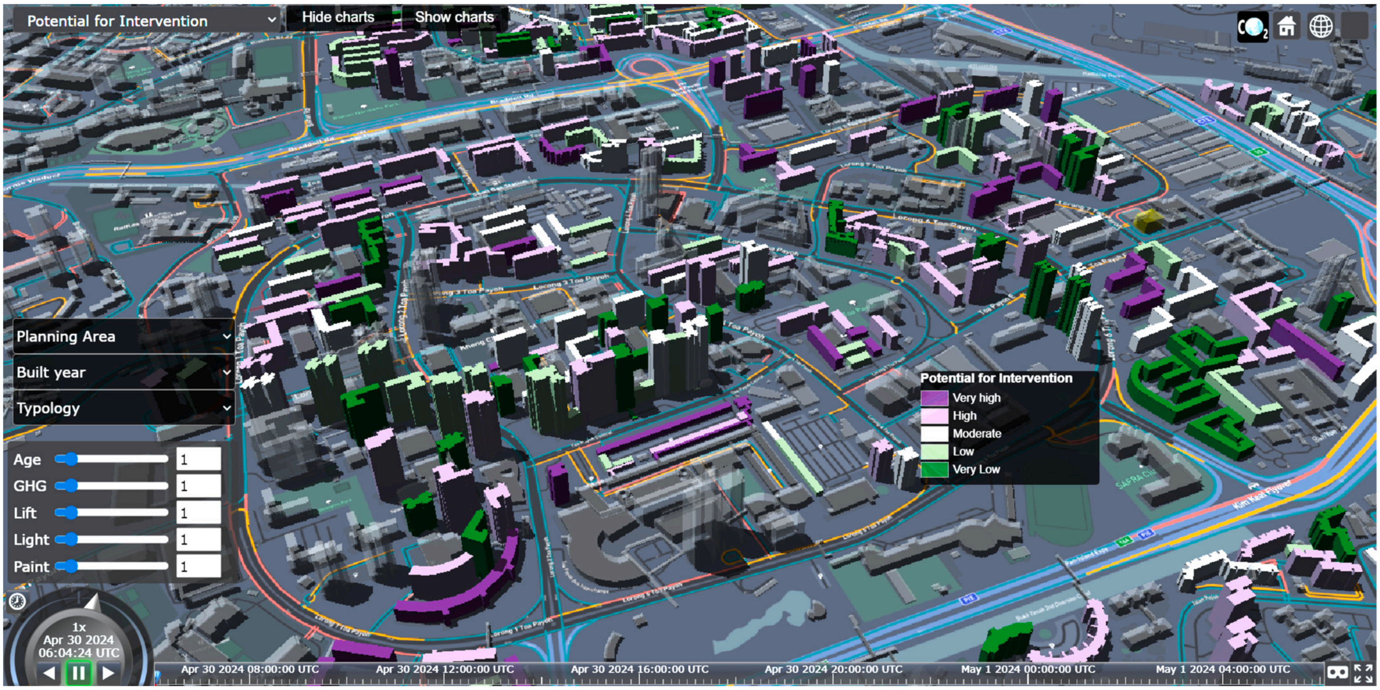

Fig. 8. Dashboard Scene 2 of GHG App showing PFI results in a heat map for sample case 1. The purple colour indicates buildings with very high PFI values and ranks, while dark green indicates very low-ranked buildings. Sliders at the bottom-left of the dashboard help users set each parameter weight, based on which PFI maps are automatically generated.

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References

[1] A.M. Toli, N. Murtagh, The concept of sustainability in smart city definitions, Front. Built Environ. 6 (2020), https://doi.org/10.3389/fbuil.2020.00077.

[2] C. Weil, S.E. Bibri, R. Longchamp, F. Golay, A. Alahi, Urban digital twin challenges: a systematic review and perspectives for sustainable smart cities, Sustain. Cities Soc. 99 (2023) 104862, https://doi.org/10.1016/j.scs.2023.104862.

[3] V.V. Lehtola, M. Koeva, S.O. Elberink, P. Raposo, J.-P. Virtanen, F. Vahdatikhaki, S. Borsci, Digital twin of a city: Review of technology serving city needs, Int. J. Appl. Earth Obs. Geoinf. 114 (2022) 102915, https://doi.org/10.1016/j.jag.2022.102915.

[4] T. Deng, K. Zhang, Z.-J.M. Shen, A systematic review of a digital twin city: A new pattern of urban governance toward smart cities, J. Manag. Sci. Eng. 6 (2021) 125–134, https://doi.org/10.1016/j.jmse.2021.03.003.

[5] M. Shahzad, M.T. Shafiq, D. Douglas, M. Kassem, Digital twins in built environments: An investigation of the characteristics, applications, and challenges, Buildings 12 (2022), https://doi.org/10.3390/buildings12020120.

[6] Z.O. Saeed, F. Mancini, T. Glusac, P. Izadpanahi, Future city, digital twinning and the urban realm: A systematic literature review, Buildings 12 (2022), https://doi.org/10.3390/buildings12050685.

[7] W. Strielkowski, G. Rausser, E. Kuzmin, Digital revolution in the energy sector: Effects of using digital twin technology, in: V. Kumar, J. Leng, V. Akberdina, E. Kuzmin (Eds.), Digital Transformation in Industry, Springer International Publishing, Cham, 2022, pp. 43–55.

[8] W. Huang, Y. Zhang, W. Zeng, Development and application of digital twin technology for integrated regional energy systems in smart cities, Sustain. Comput. Inf. Sci. 36 (2022) 100781, https://doi.org/10.1016/j.suscom.2022.100781.

[9] C. Ghenai, L.A. Husein, M. Al Nahlawi, A.K. Hamid, M. Bettayeb, Recent trends of digital twin technologies in the energy sector: A comprehensive review, Sustain. Energy Technol. Assess. 54 (2022) 102837, https://doi.org/10.1016/j.seta.2022.102837.

[10] I. Jeddoub, G.-A. Nys, R. Hajji, R. Billen, Digital twins for cities: Analyzing the gap between concepts and current implementations with a specific focus on data integration, Int. J. Appl. Earth Obs. Geoinf. 122 (2023) 103440, https://doi.org/10.1016/j.jag.2023.103440.

[11] T.T.P. Bui, S. Wilkinson, C. MacGregor, N. Domingo, Decision making in reducing carbon emissions for building refurbishment: Case studies of university buildings in New Zealand, Build. Environ. 242 (2023) 110557, https://doi.org/10.1016/j.buildenv.2023.110557.

[12] C. Dominguez, E. Kakkos, D. Gross, R. Hischier, K. Orehounig, Renovated or replaced? Finding the optimal solution for an existing building considering cumulative CO2 emissions, energy consumption and costs – A case study, Energy Build. 303 (2024) 113767, https://doi.org/10.1016/j.enbuild.2023.113767.

[13] F. Miralles-Wilhelm, Development and application of integrative modeling tools in support of food-energy-water nexus planning—A research agenda, J. Environ. Stud. Sci. 6 (2016) 3–10, https://doi.org/10.1007/s13412-016-0361-1.

[14] T. Santhanavanich, R. Padsala, P. Würstle, V. Coors, The spatial data infrastructure of an Urban Digital Twin in the building energy domain using OGC standards, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. X-4/W2–2022 (2022) 249–256, https://doi.org/10.5194/isprs-annals-X-4-W2-2022-249-2022.

[15] W.-M. Chia, M. Li, Y. Tang, Public and private housing markets dynamics in Singapore: the role of fundamentals, J. Hous. Econ. 36 (2017) 44–61, https://doi.org/10.1016/j.jhe.2017.03.001.

[16] Kai Cao, Mi Diao, B. Wu, A big data-based geographically weighted regression model for public housing prices: A case study in Singapore, Ann. Assoc. Am. Geogr. 109 (2019) 173–186, https://doi.org/10.1080/24694452.2018.1470925.

[17] Housing Development Board (HDB), Annual report 2022/2023 - Key Statistics, 2023, https://www.hdb.gov.sg/-/media/doc/CCG/Annual-Report-FY2022/HDB-Key-Statistics-FY22.ashx. (Accessed 12 July 2023).

[18] Housing Development Board (HDB), Upgrading and rejuvenating our HDB flats and estates, 2024, https://www.hdb.gov.sg/about-us/news-and-publications/publications/hdbspeaks/upgrading-and-rejuvenating-our-hdb-flats-and-estates. (Accessed 7 April 2024).

[19] Centre for Liveable Cities, Energising Singapore: balancing liveability and growth, centre for liveable cities, Singapore, 2018, https://www.clc.gov.sg/research-publications/publications/urban-systems-studies/view/energising-singapore-balancing-liveability-and-growth. (Accessed 10 November 2023).

[20] National Environment Agency (NEA), Singapore's fifth national communication and fifth biennial update report, 2022, https://www.nea.gov.sg/our-services/climate-change-energy-efficiency/climate-change/national-communications-and-biennial-update-reports. (Accessed 10 July 2023).

[21] Climate Action Tracker, Warming projections global update November 2022, 2022, https://policycommons.net/artifacts/3153102/cat_2022-11-10_globalupdate_cop27/3950927/. (Accessed 2 May 2023).

[22] B. Su, T. Goh, B.W. Ang, T.S. Ng, Energy consumption and energy efficiency trends in Singapore: The case of a meticulously planned city, Energy Policy 161 (2022) 112732, https://doi.org/10.1016/j.enpol.2021.112732.
[23] Energy Market Authority (EMA), Singapore energy statistics 2023, 2023, September, https://www.ema.gov.sg/resources/singapore-energy-statistics/chapter3. (Accessed 25 November 2023).
[24] Energy Market Authority (EMA), Singapore energy statistics 2023, 2023, September, https://www.ema.gov.sg/resources/singapore-energy-statistics/chapter2. (Accessed 25 November 2023).
[25] A. Francisco, N. Mohammadi, J.E. Taylor, Smart city digital twin-enabled energy management: Toward real-time urban building energy benchmarking, J. Manag. Eng. 36 (2020), https://doi.org/10.1061/(asce)me.1943-5479.0000741.
[26] A. Bujari, A. Calvio, L. Foschini, A. Sabbioni, A. Corradi, A digital twin decision support system for the urban facility management process, Sensors 21 (2021), https://doi.org/10.3390/s21248460.
[27] W. Wang, H. Guo, X. Li, S. Tang, J. Xia, Z. Lv, Deep learning for assessment of environmental satisfaction using BIM big data in energy efficient building digital twins, Sustain. Energy Technol. Assess. 50 (2022) 101897, https://doi.org/10.1016/j.seta.2021.101897.
[28] M. Jradi, B.E. Madsen, J.H. Kaiser, DanRETwin: A digital twin solution for optimal energy retrofit decision-making and decarbonization of the Danish building stock, Appl. Sci. 13 (2023), https://doi.org/10.3390/app13179778.
[29] C.C. Ohueri, M.A.N. Masrom, H. Habil, M.S. Ambashe, IoT-based digital twin best practices for reducing operational carbon in building retrofitting: A mixed-method approach, Eng. Constr. Archit. Manag. (2023), https://doi.org/10.1108/ecam-08-2023-0827.
[30] M. Rossknecht, E. Airaksinen, Concept and evaluation of heating demand prediction based on 3D city models and the citygml energy ADE—Case study Helsinki, ISPRS Int.l J. Geo-Inf. 9 (2020), https://doi.org/10.3390/ijgi9100602.
[31] S. Paiho, N. Wessberg, M. Dubovik, R. Lavikka, S. Naumer, Twin transition in the built environment – Policy mechanisms, technologies and market views from a cold climate perspective, Sustain. Cities Soc. 98 (2023) 104870, https://doi.org/10.1016/j.scs.2023.104870.
[32] K. Reichardt, S.O. Negro, K.S. Rogge, M.P. Hekkert, Analyzing interdependencies between policy mixes and technological innovation systems: The case of offshore wind in Germany, Technol. Forecast. Soc. Change 106 (2016) 11–21, https://doi.org/10.1016/j.techfore.2016.01.029.
[33] K.S. Rogge, K. Reichardt, Policy mixes for sustainability transitions: An extended concept and framework for analysis, Res. Policy 45 (2016) 1620–1635, https://doi.org/10.1016/j.respol.2016.04.004.
[34] F. Kern, K.S. Rogge, M. Howlett, Policy mixes for sustainability transitions: New approaches and insights through bridging innovation and policy studies, Res. Policy 48 (2019) 103832, https://doi.org/10.1016/j.respol.2019.103832.
[35] I. Savin, F. Creutzig, T. Filatova, J. Foramitti, T. Konc, L. Niamir, K. Safarzynska, J. van den Bergh, Agent-based modeling to integrate elements from different disciplines for ambitious climate policy, WIREs Clim. Change 14 (2023) e811, https://doi.org/10.1002/wcc.811.
[36] F. Chien, K.Y. Chau, M. Sadiq, Impact of climate mitigation technology and natural resource management on climate change in China, Resour. Policy 81 (2023) 103367, https://doi.org/10.1016/j.resourpol.2023.103367.
[37] A.I. Osman, L. Chen, M. Yang, G. Msigwa, M. Farghali, S. Fawzy, D.W. Rooney, P.-S. Yap, Cost, environmental impact, and resilience of renewable energy under a changing climate: a review, Environ. Chem. Lett. 21 (2023) 741–764, https://doi.org/10.1007/s10311-022-01532-8.
[38] J. Borst, Urban strategy: interactive spatial planning for sustainable cities, in: Next Generation Infrastructure Systems for Eco-Cities, 2010, pp. 1–5.
[39] S.Q. Dou, H.H. Zhang, Y.Q. Zhao, A.M. Wang, Y.T. Xiong, J.M. Zuo, Research on construction of spatio-temporal data visualization platform for GIS and BIM fusion, Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLII-3/W10 (2020) 555–563, https://doi.org/10.5194/isprs-archives-xlii-3-w10-555-2020.
[40] Q. Lu, A.K. Parlikad, P. Woodall, G.D. Ranasinghe, X. Xie, Z. Liang, E. Konstantinou, J. Heaton, J. Schooling, Developing a digital twin at building and city levels: Case study of West Cambridge campus, J. Manag. Eng. 36 (2020) 5020004, https://doi.org/10.1061/(asce)me.1943-5479.0000763.
[41] L. Raes, P. Michiels, T. Adolphi, C. Tampere, A. Dalianis, S. McAleer, P. Kogut, Duet: A framework for building secure and trusted digital twins of smart cities, IEEE Internet Comput. (2021), https://doi.org/10.1109/MIC.2021.3060962.
[42] G. Schrotter, C. Hürzeler, The digital twin of the city of Zurich for urban planning, PFG - J. Photogramm. Remote Sens. Geoinf. Sci. 88 (2020) 99–112, https://doi.org/10.1007/s41064-020-00092-2.
[43] S. Agostinelli, F. Cumo, M.M. Nezhad, G. Orsini, G. Piras, Renewable energy system controlled by open-source tools and digital twin model: Zero energy port area in Italy, Energies 15 (2022), https://doi.org/10.3390/en15051817.
[44] The CEA Team (2022), City Energy Analyst v3.32.0, 2022, https://doi.org/10.5281/zenodo.598221.
[45] Y. Chen, T. Hong, M.A. Piette, Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis, Appl. Energy 205 (2017) 323–335, https://doi.org/10.1016/j.apenergy.2017.07.128, https://www.sciencedirect.com/science/article/pii/S0306261917310024.
[46] Y.Q. Ang, Z.M. Berzolla, S. Letellier-Duchesne, V. Jusiega, C. Reinhart, UBEM.io: a web-based framework to rapidly generate urban building energy models for carbon reduction technology pathways, Sustain. Cities Soc. 77 (2022) 103534, https://doi.org/10.1016/j.scs.2021.103534, https://www.sciencedirect.com/science/article/pii/S2210670721008003.
[47] T. Hong, M.A. Piette, Y. Chen, S.H. Lee, S.C. Taylor-Lange, R. Zhang, K. Sun, P. Price, Commercial building energy saver: An energy retrofit analysis toolkit, Appl. Energy 159 (2015) 298–309, https://doi.org/10.1016/j.apenergy.2015.09.002, https://www.sciencedirect.com/science/article/pii/S0306261915010703.
[48] S.H. Lee, T. Hong, M.A. Piette, G. Sawaya, Y. Chen, S.C. Taylor-Lange, Accelerating the energy retrofit of commercial buildings using a database of energy efficiency performance, Energy 90 (2015) 738–747, https://doi.org/10.1016/j.energy.2015.07.107, https://www.sciencedirect.com/science/article/pii/S0360544215010026.
[49] National Renewbale Energy Laboratory, Openstudio 2017, 2017, https://www.openstudio.net/. (Accessed 15 July 2024).
[50] U.S. DOE BTO, Energyplus 2017, https://energyplus.net/, 2017. (Accessed 15 July 2024).
[51] C. Waibel, Z. Shi, Veggies and PV: Optimization of building-integrated agriculture in an energy hub, J. Phys. Conf. Ser. 2600 (2023) 172001, https://doi.org/10.1088/1742-6596/2600/17/172001.
[52] G. Happle, J. Fonseca, A. Schlueter, Impacts of diversity in commercial building occupancy profiles on district energy demand and supply, Appl. Energy 277 (2020) 115594, https://doi.org/10.1016/j.apenergy.2020.115594.
[53] M. Mosteiro-Romero, C. Miller, A. Chong, R. Stouffs, Elastic buildings: calibrated district-scale simulation of occupant-flexible campus operation for hybrid work optimization, Build. Environ. 237 (2023) 110318, https://doi.org/10.1016/j.buildenv.2023.110318.
[54] Z. Shi, J. Fonseca, A. Schlueter, A parametric method using vernacular urban block typologies for investigating interactions between solar energy use and urban design, Renew. Energy 165 (2021) 823–841, https://doi.org/10.1016/j.renene.2020.10.067.
[55] C. Waibel, S. Hsieh, A. Schlueter, Impact of demand response on BIPV and district multi-energy systems design in Singapore and Switzerland, J. Phys. Conf. Ser. 2042 (2021) 012096, https://doi.org/10.1088/1742-6596/2042/1/012096.
[56] L. Santos, I. Nevat, J. Ivanchev, M. Niffeler, Estimation of Buildings' Energy Efficiency via a Surrogate Regression Model, 2024, 2024012062.
[57] H.-M. Deng, Q.-M. Liang, L.-J. Liu, L.D. Anadon, Co-benefits of greenhouse gas mitigation: a review and classification by type, mitigation sector, and geography, Environ. Res. Lett. 12 (2018) 123001, https://doi.org/10.1088/1748-9326/aa98d2.
[58] P. Alva, F. Biljecki, R. Stouffs, Use cases for district-scale Urban Digital Twins, Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLVIII-4/W4-2022 (2022) 5–12, https://doi.org/10.5194/isprs-archives-xlviii-4-w4-2022-5-2022.
[59] P. Alva, M. Mosteiro-Romero, C. Miller, R. Stouffs, Digital twin-based resilience evaluation of district-scale archetypes, in: 27th International Conference on Computer-Aided Architectural Design Research in Asia: Post-Carbon, CAADRIA 2022, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 2022, pp. 525–534.
[60] P. Alva, M. Mosteiro-Romero, W. Pei, A. Bartolini, C. Yuan, R. Stouffs, Bottom-up approach for creating an Urban Digital Twin platform and use cases, in: 28th International Conference on Computer-Aided Architectural Design Research in Asia: Human-Centric, CAADRIA 2023, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 2023, pp. 605–614.
[61] M. Mosteiro-Romero, P. Alva, R. Stouffs, C. Miller, Towards occupant-driven district energy system operation: A digital twin platform for energy resilience and occupant well-being, in: PLEA 2022: Will Cities Survive? Passive and Low Energy Architecture (PLEA), November 23–25, 2022, Santiago, Chile, 2022, pp. 834–839.
[62] G.M. Zanghelini, E. Cherubini, S.R. Soares, How multi-criteria decision analysis (MCDA) is aiding life cycle assessment (LCA) in results interpretation, J. Clean. Prod. 172 (2018) 609–622, https://doi.org/10.1016/j.jclepro.2017.10.230, https://www.sciencedirect.com/science/article/pii/S0959652617325350.
[63] I. Linkov, E. Moberg, Multi-Criteria Decision Analysis: Environmental Applications and Case Studies, CRC Press, 2011.
[64] M. Doumpos, C. Zopounidis, Multicriteria Decision Aid Classification Methods, vol. 73, 1 ed, Kluwer Academic Publishers, Dordrecht, Boston, 2002.
[65] S. Pohekar, M. Ramachandran, Application of multi-criteria decision making to sustainable energy planning—A review, Renew. Sustain. Energy Rev. 8 (2004) 365–381, https://doi.org/10.1016/j.rser.2003.12.007.
[66] M. Convertino, K.M. Baker, J.T. Vogel, C. Lu, B. Suedel, I. Linkov, Multi-criteria decision analysis to select metrics for design and monitoring of sustainable ecosystem restorations, Ecol. Indic. 26 (2013) 76–86, https://doi.org/10.1016/j.ecolind.2012.10.005, https://www.sciencedirect.com/science/article/pii/S1470160X12003561.
[67] I.N. Durbach, T.J. Stewart, Modeling uncertainty in multi-criteria decision analysis, Eur. J. Oper. Res. 223 (2012) 1–14, https://doi.org/10.1016/j.ejor.2012.04.038.
[68] J.-J. Wang, Y.-Y. Jing, C.-F. Zhang, J.-H. Zhao, Review on multi-criteria decision analysis aid in sustainable energy decision-making, Renew. Sustain. Energy Rev. 13 (2009) 2263–2278, https://doi.org/10.1016/j.rser.2009.06.021.
[69] J.C. Cegan, A.M. Filion, J.M. Keisler, I. Linkov, Trends and applications of multi-criteria decision analysis in environmental sciences: literature review, Environ. Syst. Decis. 37 (2017) 123–133, https://doi.org/10.1007/s10669-017-9642-9.

[70] J.A.P. Amorocho, T. Hartmann, A multi-criteria decision-making framework for residential building renovation using pairwise comparison and topsis methods, J. Build. Eng. 53 (2022) 104596, https://doi.org/10.1016/j.jobe.2022.104596.

[71] M.D. Bostenaru Dan, Multi-criteria decision model for retrofitting existing buildings, Nat. Hazards Earth Syst. Sci. 4 (2004) 485–499, https://doi.org/10.5194/nhess-4-485-2004.

[72] Y. Ataei, A. Mahmoudi, M.R. Feylizadeh, D.-F. Li, Ordinal priority approach (OPA) in multiple attribute decision-making, Appl. Soft Comput. 86 (2020) 105893, https://doi.org/10.1016/j.asoc.2019.105893, https://www.sciencedirect.com/science/article/pii/S156849461930674X.

[73] R.T. Marler, J.S. Arora, The weighted sum method for multi-objective optimization: new insights, Struct. Multidiscip. Optim. 41 (2010) 853–862, https://doi.org/10.1007/s00158-009-0460-7.

[74] S. Sorooshian, Y. Parsia, Modified weighted sum method for decisions with altered sources of information, Math. Stat. 7 (2019) 57–60, https://doi.org/10.13189/ms.2019.070301.

[75] A. Serrano-Jiménez, P. Femenías, L. Thuvander, Á. Barrios-Padura, A multi-criteria decision support method towards selecting feasible and sustainable housing renovation strategies, J. Clean. Prod. 278 (2021) 123588, https://doi.org/10.1016/j.jclepro.2020.123588.

[76] J. Lizana, Á. Barrios-Padura, M. Molina-Huelva, R. Chacartegui, Multi-criteria assessment for the effective decision management in residential energy retrofitting, Energy Build. 129 (2016) 284–307, https://doi.org/10.1016/j.enbuild.2016.07.043.

[77] Technische Universität Berlin (TU Berlin), BIM-SPEED D7.1 multi-criteria decision making method and tool for housing renovation projects, 2020, https://depositonce.tu-berlin.de/items/99a1fb74-1a08-4d9e-be29-3bfb6be0702a. (Accessed 2 July 2024).

[78] W.-M. Wang, A.H.I. Lee, L.-P. Peng, Z.-L. Wu, An integrated decision making model for district revitalization and regeneration project selection, Decis. Support Syst. 54 (2013) 1092–1103, https://doi.org/10.1016/j.dss.2012.10.035.

[79] E.K. Zavadskas, J. Antucheviciene, Multiple criteria evaluation of rural building's regeneration alternatives, Build. Environ. 42 (2007) 436–451, https://doi.org/10.1016/j.buildenv.2005.08.001.

[80] J. Si, L. Marjanovic-Halburd, F. Nasiri, S. Bell, Assessment of building-integrated green technologies: a review and case study on applications of multi-criteria decision making (MCDM) method, Sustain. Cities Soc. 27 (2016) 106–115, https://doi.org/10.1016/j.scs.2016.06.013.

[81] C.-J. Kim, W.S. Yoo, U.-K. Lee, K.-J. Song, K.-I. Kang, H. Cho, An experience curve-based decision support model for prioritizing restoration needs of cultural heritage, J. Cult. Heritage 11 (2010) 430–437, https://doi.org/10.1016/j.culher.2010.03.004.

[82] N. Caterino, I. Iervolino, G. Manfredi, E. Cosenza, Comparative analysis of multi-criteria decision-making methods for seismic structural retrofitting, Comput.-Aided Civ. Infrastruct. Eng. 24 (2009) 432–445, https://doi.org/10.1111/j.1467-8667.2009.00599.x.

[83] D. Dirutigliano, C. Delmastro, S. Torabi Moghadam, A multi-criteria application to select energy retrofit measures at the building and district scale, Therm. Sci. Eng. Prog. 6 (2018) 457–464, https://doi.org/10.1016/j.tsep.2018.04.007.

[84] J.M.C. Ongpeng, B.I.B. Rabe, L.F. Razon, K.B. Aviso, R.R. Tan, A multi-criterion decision analysis framework for sustainable energy retrofit in buildings, Energy 239 (2022) 122315, https://doi.org/10.1016/j.energy.2021.122315.

[85] A. Velykorusova, E.K. Zavadskas, L. Tupenaite, L. Kanapeckiene, D. Migilinskas, V. Kutut, I. Ubarte, Z. Abaravicius, A. Kaklauskas, Intelligent multi-criteria decision support for renovation solutions for a building based on emotion recognition by applying the COPRAS method and BIM integration, Appl. Sci. 13 (2023), https://doi.org/10.3390/app13095453.

[86] M.A. García-Fuentes, R. García-Pajares, C. Sanz, A. Meiss, Novel design support methodology based on a multi-criteria decision analysis approach for energy efficient district retrofitting projects, Energies 11 (2018), https://doi.org/10.3390/en11092368.

[87] M. Seddiki, K. Anouche, A. Bennadji, P. Boateng, A multi-criteria group decision-making method for the thermal renovation of masonry buildings: The case of Algeria, Energy Build. 129 (2016) 471–483, https://doi.org/10.1016/j.enbuild.2016.08.023.

[88] S. Daniel, C. Ghiaus, Multi-criteria decision analysis for energy retrofit of residential buildings: Methodology and feedback from real application, Energies 16 (2023), https://doi.org/10.3390/en16020902.

[89] L. Harnot, C.B. George, Embodied Carbon in Building Services: A Calculation Methodology, Chartered Institution of Building Services Engineers, 2021.

[90] P. Cozzi, S. Lilley, OGC 3D Tiles Specification 1.1, http://www.opengis.net/doc/cs/3D-Tiles/1.1, 2023.

[91] S. Mishra, Practical Highcharts with Angular: Your Essential Guide to Creating Real-Time Dashboards, 2nd 2023, 2, 2nd second ed., Apress, Berkeley, CA, 2023.

[92] The United Nations Framework Convention on Climate Change (UNCCC), Tool to calculate the emission factor for an electricity system (version 7.0), 2018, August 31, https://cdm.unfccc.int/methodologies/PAmethodologies/tools/am-tool-07-v7.0.pdf. (Accessed 11 September 2023).

[93] Intergovernmental Panel on Climate Change (IPCC), Climate change 2021 – the physical science basis: working group I contribution to the sixth assessment report of the intergovernmental panel on climate change, 2021, https://www.ipcc.ch/report/ar6/wg1/. (Accessed 11 September 2023).

[94] The National Environment Agency (NEA), Household electricity consumption profile, 2022, https://www.nea.gov.sg/our-services/climate-change-energy-efficiency/energy-efficiency/household-sector/household-electricity-consumption-profile. (Accessed 11 August 2023).

[95] L. Georges, M. Haase, A.H. Wiberg, T. Kristjansdottir, B. Risholt, Life cycle emissions analysis of two nZEB concepts, Build. Res. Inf. 43 (2015) 82–93, https://doi.org/10.1080/09613218.2015.955755.

[96] R. Frischknecht, L. Ramseier, W. Yang, H. Birgisdottir, C.U. Chae, T. Lützkendorf, A. Passer, M. Balouktsi, B. Berg, L. Bragança, J. Butler, M. Cellura, M. Dixit, D. Dowdell, N. Francart, A.G. Martínez, V. Gomes, M.G.D. Silva, G. Guimaraes, E. Hoxha, M.K. Wiik, H. König, C. Llatas, S. Longo, A. Lupíšek, J. Martel, R. Mateus, F.N. Rasmussen, C. Ouellet-Plamondon, B. Peuportier, F. Pomponi, L. Pulgrossi, M. Röck, D. Satola, B.S. Verdaguer, Z. Szalay, A.T. Nhu, J. Veselka, M. Volf, O. Zara, Comparison of the greenhouse gas emissions of a high-rise residential building assessed with different national LCA approaches – IEA EBC Annex 72, IOP Conf. Ser. Earth Environ. Sci. 588 (2020) 022029, https://doi.org/10.1088/1755-1315/588/2/022029.

[97] The International (Environmental Product Declarations) EPD System, Midea split-type room air conditioner EPD model - MSAGBU-12HRFN8-QRD0GW, 2022, https://www.environdec.com/library/epd6897. (Accessed 28 November 2023).

[98] OpenStreetMap contributors, 2017, Planet dump retrieved from, https://planet.osm.org, https://www.openstreetmap.org. (Accessed 5 July 2023).

[99] Master Plan 2019 Land Use layer, Urban redevelopment authority (URA), 2019, Data.gov.sg., 2019, https://data.gov.sg/dataset/master-plan-2019-land-use-layer. (Accessed 11 April 2023).

[100] M. Mosteiro-Romero, D. Maiullari, M. Pijpers-van Esch, A. Schlueter, An integrated microclimate-energy demand simulation method for the assessment of urban districts, Front. Built Environ. 6 (2020) 553946, https://doi.org/10.3389/fbuil.2020.553946.

[101] Master Plan 2019 Subzone Boundary (No Sea), Urban redevelopment authority (URA), 2019, Data.gov.sg., 2019, https://data.gov.sg/dataset/master-plan-2019-subzone-boundary-no-sea. (Accessed 8 April 2023).

[102] D. Singh, B. Singh, Investigating the impact of data normalization on classification performance, Appl. Soft Comput. 97 (2020) 105524, https://doi.org/10.1016/j.asoc.2019.105524.

[103] Housing Development Board (HDB), Home improvement programme (HIP), 2020, https://www.hdb.gov.sg/residential/living-in-an-hdb-flat/sers-and-upgrading-programmes/upgrading-programmes/types/home-improvement-programme-hip. (Accessed 12 November 2023).

[104] Housing Development Board (HDB), Lift upgrading programme (LUP), 2020, https://www.hdb.gov.sg/residential/living-in-an-hdb-flat/sers-and-upgrading-programmes/upgrading-programmes/types/lift-upgrading-programme. (Accessed 12 November 2023).

[105] Ministry of National Development (MND), Town councils, 2020, https://www.mnd.gov.sg/our-work/regulating-town-councils/about-town-councils. (Accessed 12 November 2023).

[106] Housing Development Board (HDB), Green towns programme, 2024, https://www.hdb.gov.sg/about-us/our-role/smart-and-sustainable-living/Green-Towns-Progamme. (Accessed 7 April 2024).

[107] M.Y. Chew, Façade inspection for falling objects from tall buildings in Singapore, Int. J. Build. Pathol. Adapt. 41 (2023) 162–183, https://doi.org/10.1108/IJBPA-10-2020-0087.

[108] International Energy Agency, IEA EBC - Annex 89 - Ways to implement net-zero whole life carbon buildings, 2023, https://annex89.iea-ebc.org/. (Accessed 5 September 2024).