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DATA SCIENCE APPLICATIONS FOR CARBON FOOTPRINT MANAGEMENT IN BUILDINGS: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Buildings have a significant impact on climate change. The building industry is the world's biggest energy consumer and the building's operation accounts for 80–90% of its total energy consumption over its lifetime. Data-driven solutions for the management of carbon footprint in buildings have great potential due to the data science field's rapid growth and the expansion of operational building data availability. Therefore, this study's aim is set as to investigate the potential applications of data science for the management of carbon footprint in buildings. The study adopted a systematic literature review as a research methodology. Accordingly, 31 publications were reviewed using the content analysis technique. The study revealed that facilitating pre-process of the operational data of buildings, fault detection and diagnosis, implementing waste management in buildings, conducting the building energy performance modelling, conducting the parametric analysis at the design phase, evaluating the energy efficiency of building designs, benchmarking evaluation, control optimisation and retrofitting analysis are the major applications of data science to the management of carbon footprint in buildings. Moreover, the study suggested carrying more studies should be done on automating and building operational data pre-processing tasks, gathering sufficient labelled data for all possible faulty operations and applying modern big data management tools and advanced analytics techniques lead to improve the applications of data science in the built environment. The results from this study provide better guidance to building sector stakeholders, information technology sector stakeholders, academic persons, non-governmental organisations (NGOs) and other relevant authorities to address the carbon footprint in buildings using data science applications.

Keywords: *Building; Carbon footprint; Data Science; Energy; Management.*

1. INTRODUCTION

All facets of human life are disrupted by the worldwide phenomenon due to climate change (Evans, 2019). These include things like warming climates, increasing sea levels, and an increase in the frequency of extreme weather events. These modifications have an

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impact on all facets of the world (Lu, 2021). Increased amounts of greenhouse gases (GHG) in the atmosphere are the primary reason why the climate is changing more dramatically than it does naturally (Radlbeck et al., 2004). The building industry has overtaken transportation as the world's biggest energy consumer, accounting for more than a third of global energy consumption (Fan et al., 2019). Since a building's operation accounts for 80–90% of its total energy consumption over its lifetime and the majority of defects manifest themselves during this phase, there are significant possible benefits from improving a building's energy efficiency (Fan et al., 2019). Environmental impact of buildings occurs at different stages of their life cycle: planning, construction, operation, renovation and demolition, with operation stage accounting for largest percentage, with approximately 85% of GHG emissions (Akbarnezhad & Xiao, 2017). In addition to that, Akbarnezhad and Xiao (2017) stated that embodied carbon also emitted considerable amount of GHG emissions. Therefore, buildings have a significant impact on global sustainability and climate change (Fan et al., 2021). Hence, the adaption of necessary actions to reduce carbon footprint (CFP) in the construction industry fundamentals (Sander et al., 2022). According to Akbarnezhad and Xiao (2017), low-carbon materials; material minimisation and material reduction strategies; material reuse and recycling strategies; local sourcing and transport minimisation; and construction optimisation strategies can be applied to reduce the embodied carbon of buildings.

In addition, the adaption of energy efficiency systems, the use low carbon construction materials, buildings retrofitting, the use of clean fuel and energy for buildings operation, the proposal of energy efficient alternative designs, the adaption of green building techniques mentioned in the green rating tools around the globe, implement proper waste management techniques, use of more energy efficient machinery and equipment and control the energy management of buildings are main strategies that can be implemented to reduce both embodied and operational carbon in buildings (Chen et al., 2022; Fu et al., 2023; Robati et al., 2021). However, previous studies showed the lack of an internationally comparable and agreed data inventory and assessment methodology which hinders the application of life cycle assessment (LCA) from the perspective of environmental concerns within the building industry (Khasreen et al., 2009). Yeheyis et al. (2013) stated that it is difficult to apply proper waste management process to the construction industry due to lack of construction data. Moreover, Hong et al. (2015) revealed that the lack of detail on and off-site process data is the main barrier to calculating embodied carbon (EC) in China. In addition to that Moncastera and Songb (2012) showed the lack of existing buildings data to conduct a comparative review of new designs CFP another challenge to managing CFP in buildings.

Technology has improved in many different fields throughout the years, and wide range of applications of the new technologies in the built environment increased (Fan, Liu, et al., 2021). It has been significantly impacted by advancements in a variety of ICT fields, including Control and Automation, Smart Metering, Real-time Monitoring, and Data Science (Fan, Yan, et al., 2021). As it is generally known, data scientists use algorithms and systems to extract information from massive amounts of data, identify patterns, and produce insightful conclusions and forecasts. It includes every stage of the data analysis process, from data cleaning and extraction through data analysis, description, and summary (Inibhunu & Carolyn McGregor, 2020). The prediction of new values and their visualisation are the outcomes. Thus, data science uses information technology techniques along with mathematical and statistical analysis (Fan et al., 2021). In order to extract knowledge, identify patterns, and produce insightful conclusions and predictions from massive amounts of data, data scientists create systems and algorithms (Zhou et al., 2013). It includes every stage of the data analysis process, from data cleaning and extraction to data analysis, description, and summary. The prediction of new numbers and their visualisation are the outcomes (Silva et al., 2017). Data science, therefore, combines information technology tools with mathematical and statistical research (Nguyen & Aiello, 2013). Accordingly, massive on-site measurements can now be easily accessed, stored, and analysed using recent developments in information technology and data science. This has led to the emergence of a new big-data-driven research model (Fan et al., 2021). In addition to that Fan et al., (2021) revealed there are now many chances to create data-driven solutions for intelligent building energy management using data science field's rapid development and the expansion of building operational data availability (Fan et al., 2021). Moreover, exploring the potential for energy savings through data-driven approaches has become simpler due to advancements in data mining technology and the broad availability of operational data on buildings (Fan et al., 2021). Ramesh et al. (2010) showed predictive modelling, fault detection and diagnosis, and control optimisation are just a few examples of how tasks connected to building energy management can benefit greatly from the knowledge found in massive building operational data. Therefore, this paper aims to explore data science applications for building carbon footprint management in the global context using a systematic literature review approach. The paper is structured as follows. First, it provides the steps of the methodology approach. Next, research findings are revealed based on a systematic literature review. Furthermore, it is followed by the conclusions and way forward.

2. METHODOLOGY

In order to develop a thorough understanding of studies by analysing themes, highlighting trends, finding gaps, and ultimately offering directions for future research, the systematic review method was considered to be appropriate (Mishra et al., 2021; Paul & Feliciano-Cestero, 2021; Paul & Singh, 2017; Rosado-Serrano et al., 2018). As a result, this research adopted a systematic review methodology to explore data science for building CFP management in the global context. Accordingly, the systematic literature review was conducted based on the methodology proposed by Denyer & Tranfield (2009). It consisted of two steps: (1) identification; and (2) screening and eligibility, as illustrated in Figure 1.

2.1 IDENTIFICATION

The identification process consists of two main phases such as choosing the database and choosing the most pertinent keywords. Accordingly, the Web of Science and Scopus were the sources of the data used in this research. One of the biggest databases of peer-reviewed literature on the globe is the Web of Science. Authoritative, multidisciplinary coverage from more than 12,000 high impact research journals globally is offered by the world's top citation databases (Sweileh et al., 2014). Additionally, with more than 49 million registered individuals, Scopus is the most peer-reviewed database worldwide (Dangelico, 2016). After the selection of databases, a list of keywords is chosen based on the review of the initial literature search. As the final step in developing keywords for the search, search-field descriptors and wildcard characters and Boolean operators were applied to the identified keywords and index terms in the logic grid shown below.

("building*" OR "construction" OR "built environment") AND ("data science") AND ("carbon management" OR "carbon reduc*" OR "carbon minimis?ation" OR "carbon management strateg" OR "net-zero carbon" OR "GHG*" OR "carbon emission" OR "net-zero emission" OR "net-zero energy" OR "smart building" OR "smart construction" OR "smart building management" OR "smart built environment")

By using the keywords mentioned above, 28 documents from Web of Science and 24 documents from Scopus appeared in the result. Then the study limited the search to document type (journal articles, review articles and conference papers) and the language was limited to English only to minimise publication bias (Mahood et al., 2014; Paez, 2007). Similarly, subsequent stages of data collection were performed to exclude duplication, filtering to the publication period from January 2015 to March 2023. After all exclusions, 47 documents were selected for the screening and eligibility phase.

2.2 SCREENING AND ELIGIBILITY

Some publications that are not very informative for this study analysis are unavoidably included in the search results due to the similarity of the keywords and the wide scope of the search. Two rounds of screening and eligibility were conducted in this respect: Titles and abstracts were checked as part of the initial filtering process. The full-text content was examined for the final round of screening, with an emphasis on the uses of data science for managing buildings CFP in a global context. After this stage, 31 publications were selected as the sample of this study. Accordingly, 31 publications were selected as the final sample of this study. The manual content analysis was adapted as an analysis technique for this study.

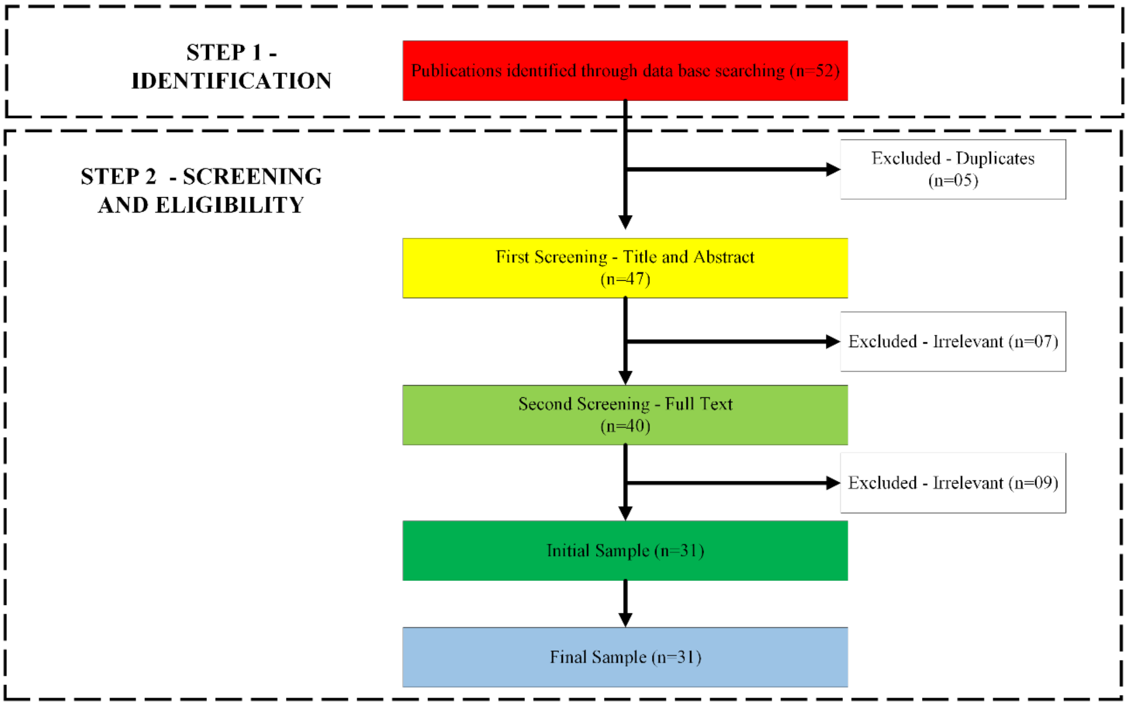

Figure 1: Process of the systematic literature review

3. FINDINGS AND DISCUSSION

This part presents and evaluates the studies' findings. The articles chosen for the current systematic review are examined in terms of their nature and changes over time. As a result, the first stage of this research identified potential data science applications for managing CFP in the building sector. The possible challenges and solutions in implementing data science for the building industry were then outlined.

3.1 GENERAL OBSERVATION OF REVIEWED ARTICLES

According to the selected 31 publications, 18 papers were journal articles and 13 papers were conference proceedings. In addition to that, when considering the chronological distribution of reviewed articles, 2015 (n=01), 2016 (n=04), 2017 (n=04), 2018 (n=04), 2019 (n=04), 2020 (n=02), 2021 (n=07) and 2022 (n=05) were published. Therefore, it is evident that the research interest was increased during last five years since 22 publications out of 31 were published in the last five years.

3.2 APPLICATIONS OF DATA SCIENCE FOR THE MANAGEMENT OF CFP IN BUILDINGS

Through the systematic literature review, it was identified that facilitating to pre-process of buildings' operational data required for GHG emission analysis, identifying the fault detection and diagnosis (FDD) of energy systems of buildings, improving the process of waste management in buildings, improving the building energy performance modelling (BPS), to conduct the parametric analysis at the design phase, to propose the more energy efficient designs, to conduct benchmark evaluation, to implement the energy efficient operational strategies to the buildings and to conduct the retrofitting analysis of buildings are the major applications of data science for the management of CFP in buildings.

3.2.1 Facilitate Pre-process of the Operational Data of Buildings

Buildings' operational carbon directly link to the energy consumption of the buildings (Wang et al., 2022). As revealed in previous studies, the management of energy consumption led to managing the CFP of buildings (Chen et al., 2022; Fu et al., 2023; Robati et al., 2021). Ramesh et al. (2010) showed operational data of buildings is essential to the management of buildings' energy consumption. Moreover, Fan et al. (2021) revealed that maintaining the buildings' operational data manually is time, labour and cost consuming. Therefore, Fan et al. (2021) revealed that data-driven solutions for intelligent building energy management have a lot of potential using the data science and the expansion of operational building data availability. Pre-processing of data lays the groundwork for reliable data analytics (Fan et al., 2021). Because operational building data are frequently of poor quality, data pre-processing is frequently required to guarantee the accuracy of data analysis using various methods. It may take up 80% of all data mining efforts and is generally acknowledged as a non-trivial task in data analysis (Cui et al., 2018). Given the generally poor data quality and the inherent complexity of building processes, data pre-processing can be very difficult in the building context. To guarantee the validity and dependability of the outcomes of data analysis, data pre-processing is frequently required. For instance, due to flaws in data gathering, transmission, and storage, building operational data usually have a lot of missing values and outliers (Cui et al., 2018; Xiao & Fan, 2014). To eliminate outliers and fill in missing values for a more trustworthy data analysis, a pre-processing phase can be applied to the data. Most data mining programs also have certain specifications for the data they can accept as input. For instance, numerical data about electricity, temperature, humidity, flow rates, and pressures make up the majority of building operational data (Fan et al., 2015).

Moreover, Fan et al. (2021) study also outlines three sophisticated data pre-processing methods for creating operational data analysis, namely data augmentation, transfer learning, and semi-supervised learning. The potential data shortage issue in specific buildings can be addressed using data augmentation and transfer learning techniques. These techniques can significantly improve the generalisation and dependability of data-driven models. Meanwhile, massive amounts of unlabelled data can be completely utilised using semi-supervised learning to fully unlock their value. As determining labels for building operational data, such as whether a data sample corresponds to normal or defective operations, can be very expensive and labour-intensive, it is particularly helpful when developing classification models for building systems (Fan et al., 2021).

3.2.2 Fault Detection and Diagnosis

To guarantee the best performance of systems and maximise energy efficiency, fault detection and diagnosis (FDD) schemes that are automatic, fast to react, accurate, and reliable are highly desirable (Khan et al., 2013). Andriamamonjy et al. (2018) stated FDD is crucial for managing the building's energy system in real-time in the construction industry and is closely linked to big data collected from the system's sensors, such as the chiller, pumps, fans, AHUs, and indoor environmental parameters (Andriamamonjy et al., 2018). Moreover, FDD plays a crucial role in ensuring building sustainability (Gholamzadehmir et al., 2020; Sha et al., 2019). Accordingly, Gholamzadehmir et al. (2020) revealed as equipment, actuator, and sensor faults in AHU operations can result in 15–30% energy savings, and it is essential to use FDD. Moreover, Fan et al. (2021) investigates the value of semi-supervised learning in detecting unseen faults during AHU operations and the study revealed that AHUs' FDD must be precise and reliable because they have a significant impact on a building's ability to regulate its indoor environment and energy efficiency.

3.2.3 Improve the Waste Management in Buildings

In the built environment, recycling, landfilling, and incineration are the three main waste control methods (Kucukvar et al., 2014). However, Kucukvar et al. (2014) revealed that the only method of reducing the carbon, energy, and water footprints of building materials was recycling. For the categories of water and energy footprint, incineration is a better option after recycling, whereas landfilling is found to be a marginally better strategy when carbon footprint is the primary emphasis of comparison. Therefore, the proper waste management implementation leads to reduce the CFP in buildings (Aadal et al., 2013). As mentioned by Yeheyis et al. (2013), lack of the construction data is main barrier to implement suitable waste management techniques in built environment. However, Andriamamonjy et al. (2018) revealed, the real time data of buildings can be extracted using data science and such data can be used to implement proper waste management techniques (Silva et al., 2017). Accordingly, Silva et al. (2017) revealed that Big Data analytics lead to improve waste management in buildings as well as in smart cities.

3.2.4 Improve the Building Energy Performance Modelling

Building energy performance modelling (BPS) has established itself as a vital method for assessing and improving building operations, which enhances building energy system management (Harish & Kumar, 2016). The assessment and optimisation of building energy system design (Attia et al., 2012), the development and assessment of operational control and optimisation strategies of building systems (Coakley et al., 2014; Li & Wen, 2014), and policy making on building regulations and power grid (Chung, 2011) have all benefited from the long-standing research and development of traditional physics-based BPS over the past 40 years (Foucquier et al., 2013). BPS typically builds on physical principles, thermodynamics, as well as heat and mass transfer, and heavily relies on meteorological data and detailed building information, such as the building's configuration and properties, its air conditioning system's design and operational parameters, and its occupants' energy-related behaviours (Tian et al., 2021). Amasyali and El-Gohary (2018) emphasised large high-rise buildings with complex structures and numerous uses have recently become more common due to urbanisation’s growth and advancements in building technology. The job of preparing the inputs for the BPS of such buildings has grown cumbersome and time-consuming (Amasyali & El-Gohary, 2018). Large buildings, meanwhile, are supported by intricate energy systems that create the ideal indoor environment (Zhao & Magoulès, 2012). Building energy modelling has become increasingly difficult due to the coupled impacts of the building envelope, energy systems, automated management systems, and climate conditions (Xiao & Fan, 2014). In these circumstances, a data-driven approach is particularly interesting because it can rapidly learn the building energy behaviour from the building operation data and needs little prior knowledge of building and energy system configurations and integrations (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019).

3.2.5 Conduct the Parametric Analysis at the Design Phase

Elbeltagi et al. (2017) mentioned due to the worry over CFP in buildings, there has been a significant increase in demand for sustainable building design and construction. Rising energy prices and growing environmental worries, especially GHG emissions, are the driving forces behind this demand. As a result, it is crucial to assess building energy usage, which is the main obstacle to reducing building energy use (Hollberg et al., 2018). When addressing the building envelope and orientation in the early design stage, the designers are hampered by the constraints of energy simulation tools (Elbeltagi et al., 2017). Accordingly, the parametric analysis provides the greatest potential for optimising the energy efficiency of buildings in the early design stages (Hollberg et al., 2018).

Accordingly, the typical patterns of energy use in residential and non-residential structures have been extensively researched (Escobar et al., 2020). It is now feasible to collect hourly or sub-hourly data from a huge number of households using the promotion of smart meters in homes (Zhou, Yang, & Shen, 2017). This data is used to support pattern analysis. Numerous methodologies, including clustering-based algorithms (Zhou, Yang, & Shao, 2017) and big data algorithms (Satre-Meloy et al., 2020), were used to obtain such data. Such studies typically result in typical energy use profiles, which are a collection of average energy use curves that help people better understand how much energy is consumed by different types of buildings. These profiles are then used as input schedules for building energy models used in simulations during the design phase as parametric analysis (Fan et al., 2021).

3.2.6 Evaluate the Energy Efficiency of Building Designs

To calculate the energy balance, various energy simulation programmes are adopted, which may result in higher measurement accuracy for building energy efficient buildings

(Ustinovichius et al., 2018). Therefore, some researchers have substituted data-driven models for physics-based models during the design process due to the shortcomings of physics-based building simulation models (Sha et al., 2019). In addition to that, Sha et al. (2019) mentioned researchers perform correlation analysis or sensitivity analysis to identify the most pertinent factors that influence the building energy consumption for a particular instance, which helps to simplify the model. After that, trained and verified data-driven models based on machine learning algorithms are used to regress the energy usage with chosen features (Sha et al., 2019). Building management system (BMS) data from actual buildings is used in the model's training (Zhan et al., 2020). The suggested model will then be applied to support the design phase evaluation of energy efficiency (Tian et al., 2021).

3.2.7 Benchmarking Evaluation

In comparison to other structures of the same type, benchmarking refers to the assessment and rating of a building's energy use efficiency (Pérez-Lombard et al., 2009). To effectively apply benchmark analytics, it is necessary to comprehend the current state of the building's energy distribution (Yang et al., 2018). These applications typically involve commercial or public buildings. Big data analysis sheds light on this viewpoint. The trained model can be used to predict the expected value or range of building energy use indicators (EUIs), based on which the energy efficiency of the building is rated (Papadopoulos & Kontokosta, 2019).

3.2.8 Control Optimisation

Control minimisation has always been a major problem in managing building energy systems. The building energy systems' big data analytics are heavily reliant on the control strategy, especially a real-time control strategy. After that, control techniques are used to attain environmental comfort and energy efficiency (Fan et al., 2021). Accordingly, the study identified that a data-driven model can be used for thermal-comfort-based environment control and energy-efficient-oriented system control optimisation.

- Thermal-comfort-based environment control

Real-time equipment management is one of the fundamental uses of building system control, used to improve indoor environment regulation and user comfort. The physics-based thermal balance model may not attain considerable accuracy in thermal comfort prediction due to the diversity and complexity of occupants' thermal comfort preferences (Giama & Papadopoulos, 2020). However, data-driven models are capable of learning and correcting the models under various application contexts because they are based on real monitoring data and environmental parameters (Amasyali & El-Gohary, 2018). In addition to that, Dinarvand et al. (2018) developed an automated approach based on probabilistic machine learning to model and predict energy consumption using occupancy data for energy efficiency management in non-domestic buildings to manage the indoor environmental quality of the buildings in the UK.

- Energy-efficient-oriented system control optimisation

Before using strategic optimisation, which has been a hot subject in recent studies, building energy prediction is required. Many energy prediction models are data-driven (Tang et al., 2020), combining data with building physics knowledge to increase prediction accuracy and provide trustworthy information for the following stage of control optimisation (Zakula et al., 2014). Moreover, Dinarvand et al. (2018) developed an automated approach based on probabilistic machine learning to model and predict energy consumption using occupancy data for energy efficiency management in non-domestic buildings to manage the energy consumption of the buildings in the UK.

3.2.9 Retrofitting Analysis

Older building renovations will significantly affect the commitment made by construction industry stakeholders to lower CO_2 emissions (Nowak & Skłodkowski, 2016). In addition, urban planning has always viewed retrofitting analysis of existing structures from a district or city scale as being essential. Cross-comparing various building properties is necessary for the evaluation of various retrofitting methods (Moazami et al., 2016). In order to discover their correlations, researchers taught data-driven models using building EUIs and building properties from large samples (Sanhudo et al., 2018). Re Cecconi et al. (2019) presented various data-driven methods to support regional energy retrofit policy when applied to school buildings as part of a regional-scale retrofit analysis. In order to assess the energy-saving potential of retrofitting steps for numerous buildings at a regional level, a data-driven approach is very cost-effective. Big data analytics' benefit is that the model is trained using actual energy consumption data from existing buildings, preventing a discrepancy between the outcomes of simulations and actual consumption (Fan et al., 2021).

3.3 CHALLENGES AND SOLUTIONS TO ADAPT DATA SCIENCE APPLICATIONS FOR BUILDINGS

As discussed above the second phase of the analysis was focused on identifying the challenges and solutions to adapt data science for buildings.

3.3.1 Complexity and Various Natures of the Buildings

Due to the wide variations in building operating characteristics and data quality, Fan, Chen, et al. (2021) stated that the data pre-processing for operational building data cannot be completely automated. Currently, it is more of a trial-and-error procedure that heavily relies on the practical tasks at hand and domain expertise. To increase the effectiveness of data analysis, more studies should be done on automating and building operational data pre-processing tasks.

3.3.2 Lack of Sufficient Labelled Data

One essential challenge in creating accurate and reliable FDD classification models is the lack of adequate labelled data. In reality, it can be highly time-consuming, labour-intensive and sometimes even infeasible to gather sufficient labelled data for all possible faulty operations (Fan et al., 2021).

3.3.3 Storage and Analysis of a Large Amount of High-Speed Real-Time Buildings Data

Bashir and Gill (2016) identified that storage and analysis of a large amount of high-speed real-time buildings data is a challenging task for big data analytics. Several modern Big Data management tools and advanced analytics techniques can be used to address this issue (Bashir & Gill, 2016).

Based on the above findings, a conceptual framework to improve the data science applications for management of carbon footprint in buildings was developed and shown in Figure 2.

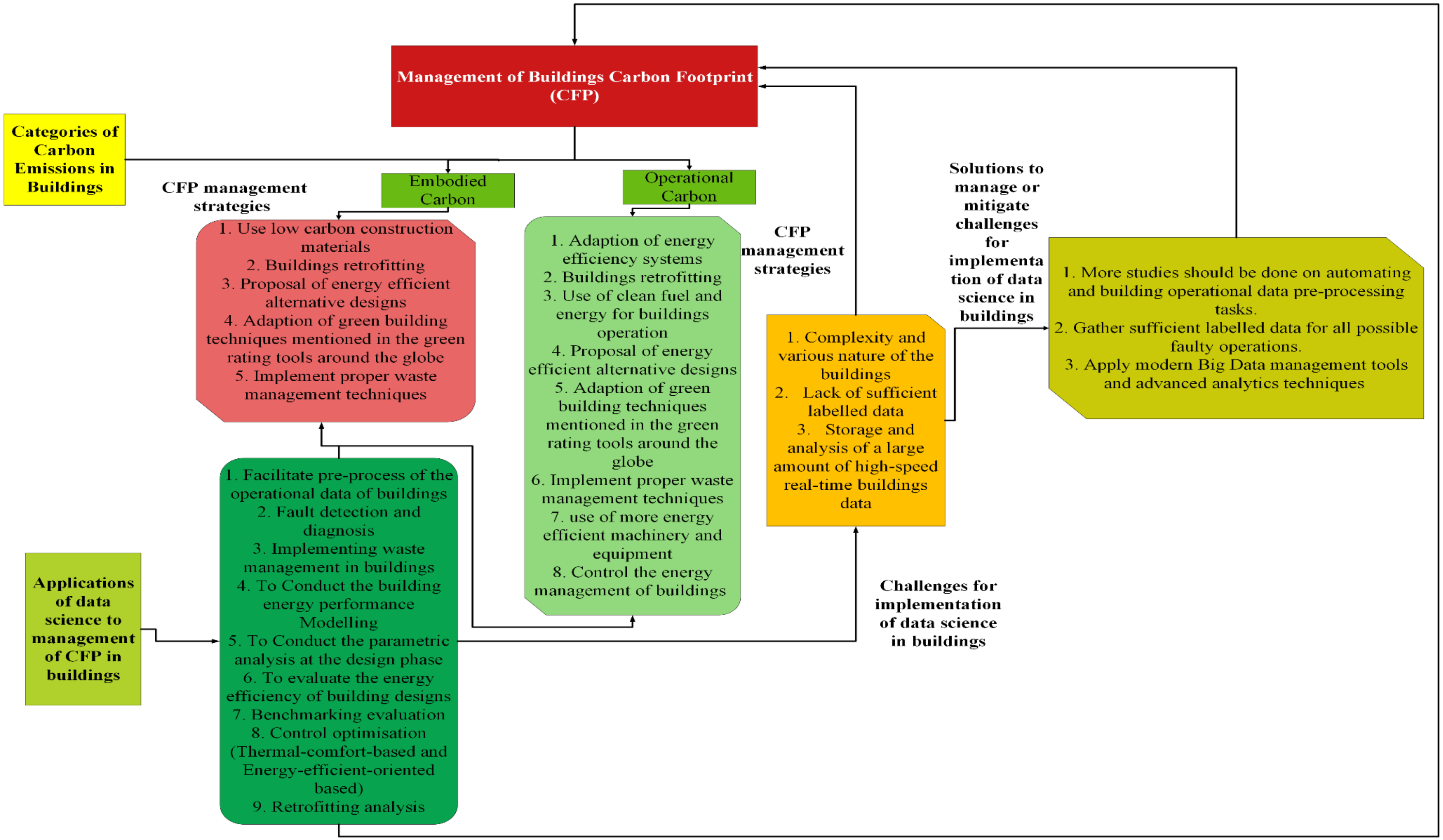

Figure 2 – A proposed conceptual framework for improve the Data science applications to management of building' carbon footprint

4. CONCLUSIONS

The main aim of this study is to investigate the data science applications for the management of CFP in buildings. Accordingly, the study concluded that facilitating pre-process of the operational data of buildings, fault detection and diagnosis, implementing waste management in buildings, conducting the building energy performance modelling, conducting the parametric analysis at the design phase, evaluating the energy efficiency of building designs, benchmarking evaluation, control optimisation and retrofitting analysis are the major applications of data science to the management of CFP in buildings. In addition, the study concluded that complexity and varied nature of the buildings, lack of sufficient labelled data and storage, and analysis of a large amount of high-speed real-time buildings data are the main challenges to implementing data science in the building sector. However, above challenges can be managed by carrying out more studies on automating and building operational data pre-processing tasks, gathering sufficient labelled data for all possible faulty operations and applying modern Big Data management tools and advanced analytics techniques.

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