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Review

A review on sustainable construction management strategies for monitoring, diagnosing, and retrofitting the building's dynamic energy performance: Focused on the operation and maintenance phase

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HIGHLIGHTS

- This study reviews the state-of-the-art in "energy" as well as "building".
- Building's dynamic energy performance should be managed in the built environments.
- This study summarizes recent progress in the building's dynamic energy performance.
- The major phases can be categorized into monitoring, diagnosing, and retrofitting.
- This study proposes the specific future development directions and challenges by phase.

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ABSTRACT

According to a press release, the building sector accounts for about 40% of the global primary energy consumption. Energy savings can be achieved in the building sector by improving the building's dynamic energy performance in terms of sustainable construction management in the urban-based built environments (referred to as an "*Urban Organism*"). This study implements the concept of "*dynamic approach*" to reflect the unexpected changes in the climate and energy environments as well as in the energy policies and technologies. Research in this area is very significant for the future of the building, energy, and environmental industries around the world. However, there is a lack of studies from the perspective of the dynamic approach and the system integration, and thus, this study is designed to fill the research gap. This study highlights the state-of-the-art in the major phases for a building's dynamic energy performance (i.e., monitoring, diagnosing, and retrofitting phases), focusing on the operation and maintenance phase. This study covers a wide range of research works and provides various illustrative examples of the monitoring, diagnosing, and retrofitting of a building's dynamic energy performance. Finally, this study proposes the specific future developments and challenges by phase and suggests the future direction of system integration for the development of a carbon-integrated management system as a large complex system. It is expected that researchers and practitioners can understand and adopt the holistic approach in the monitoring, diagnosing, and retrofitting of a building's dynamic energy performance under the new paradigm of an "*Urban Organism*".

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1. Introduction

1.1. Research background and motivation

According to the *2013 Survey of World Energy Resources* published by World Energy Council, the global primary energy demand may increase by over 50% by 2050, and at least 80% of the increase is expected to be seen in the developing countries. Particularly, the total primary energy demand in China is projected to increase twofold by 2035. Although the global energy resources can be shown to be sufficient at this point, some specialists forecast that the world's fossil fuel reserves would be depleted within 50 years in considering the increase rate of the global primary energy demand [1–3]. Meanwhile, regarding the global energy resources, global environmental issues such as global warming are considered very important, and the nuclear power plant disaster in Fukushima, Japan has raised the issue of radioactive pollution [4]. Thus, there is a need to use clean technologies to address such potential problems. Toward this end, significant capital investments should be made, and the global energy consumers should be ready to pay higher fees than they are currently paying for utility power.

The building sector accounts for about 40% of the global primary energy demand, and it is estimated that the potential energy savings that would be achieved in the building sector is between 20% and 40% [5–8]. Various institutions have been established worldwide to realize energy-efficient and low-emission buildings. One of the most representative institutions is Energy Performance of Building Directive (EPBD), established on December 16, 2002 in the European Union. EPBD forces building purchasers and tenants to provide the energy performance certificate (EPC) in the building sale or rental process so as to strengthen the management of the total energy consumption in the building sector. Ultimately, EPBD aims to achieve the potential energy savings in the building sector [9,10]. Particularly, such policy aims to monitor and diagnose the energy performance in the operation and maintenance phase of the building sector.

To make such policy more effective, it is required to consider the building's energy performance under the new paradigm of an "*Urban Organism*" [11]. In this paradigm, the building's energy performance can be relatively recognized and evaluated by the following various factors in the urban-based built environments; and therefore, it should be managed in terms of the "*dynamic approach*".

- The increase in the global warming potential as one of the environmental impacts has an effect on the increase in the heating and cooling demands of the existing buildings, which can change the energy consumption patterns of residents.
- Due to the decrease in the world's fossil fuel reserves for the energy supply, the energy price continues to increase; and thus, it can have an effect on the energy consumption patterns of residents.
- The energy consumption patterns of residents can be affected by various energy policies such as the carbon emissions reduction target (which has been implemented around the world to reduce greenhouse gas (GHG) emissions), the emissions trading

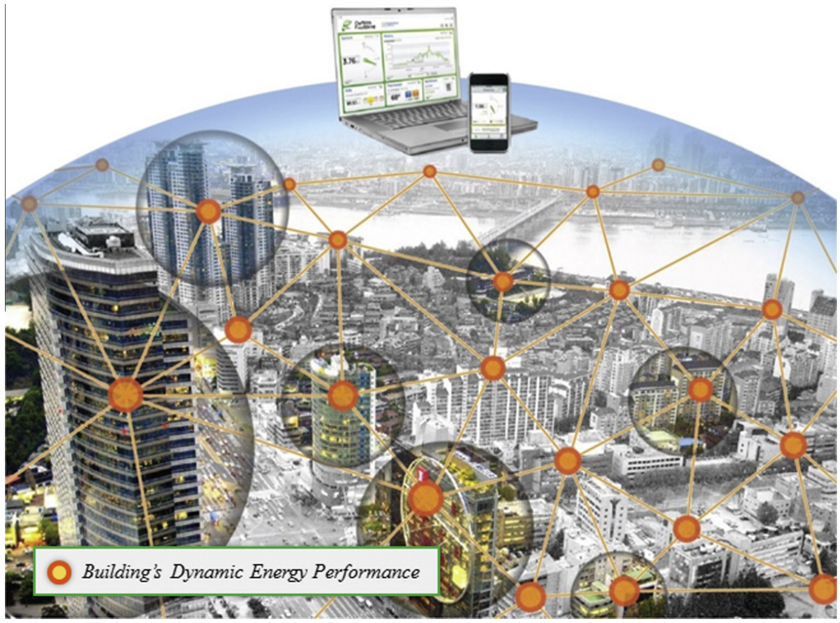

Fig. 1. Concept of an "*Urban Organism*".

scheme (which has been implemented as a market-based approach to control and reduce the GHG emissions by providing carbon credits as an economic incentive), and the EPC (which should be provided in the building sale or rental process).

- The building's physical performance continues to decrease over its life-cycle; and thus, it is critical for residents to maintain and improve the building's energy performance using the latest technologies in the sustainable way across its entire life cycle.

Therefore, it is required to implement the concept of "*dynamic approach*" to reflect the aforementioned unexpected changes in the climate and energy environments as well as in the energy policies and technologies under the new paradigm of an "*Urban Organism*". Based on this background, this study defined the following two concepts [11].

- First, in the evaluation of a building's energy performance, a building in a city is required to be recognized as a living being like human from a macroscopic perspective rather than a single building from a microscopic perspective. In addition, it should be considered that the energy performance of a certain building is closely related to the other building's energy performance. This is because the building's energy performance in the urban-based built environments can be relatively recognized and evaluated by comparing it to the others, which can cause change the energy consumption patterns of residents. That is, based on the urban-based energy policy such as the EPC, the building's energy performance should be treated from the relative perspective rather than the absolute perspective. This study refers to this concept as an "*Urban Organism*", which is a new paradigm for sustainable construction management in the urban-based built environments (refer to Fig. 1).
- Second, as a person's health condition should be managed throughout his lifetime, the building's energy performance should be considered during the building's lifecycle, from the concept of "*Cradle to Grave*". That is, as the health condition of a person should be monitored, diagnosed, and operated if he has any kind of health problem since he was born, the building's energy performance should be monitored, diagnosed, and retrofitted to solve the diagnosed problems (e.g., excessive energy consumption) (refer to Fig. 2). This study focused on the operation and maintenance phase of the building sector (refer[1] to the red boxes in Fig. 2).

Based on the new approaches mentioned above, this study aims to highlight the state-of-the-art in the major phases for a building's dynamic energy performance (i.e., monitoring, diagnosing, and retrofitting phases), focusing on the operation and maintenance phase. Research in this area is very significant for the future of the building, energy, and environmental industries around the world, but there is a lack of studies that were conducted from the perspective of the dynamic approach and the system integration, and thus, this study is designed to fill the research gap. Particularly, in terms of the system integration, this study carefully examines the extensive types of data that should be considered in each phase, the applicable methodologies and technologies that can be used in each phase, and the interrelation among the information that can be made in each phase.

Ultimately, it is expected that this study will allow researchers, practitioners, and policymakers to understand the dynamic approach for maintaining the building's energy performance and to adopt the holistic approach for developing the *Carbon Integrated Management System for monitoring, diagnosing and retrofitting the building's dynamic energy performance in a City, an urban organism (CIMSCity)* so as to minimize the carbon emissions in the operation and maintenance phase of the building sector [11–20]. In short, this study implements the concept of "*dynamic approach*" for monitoring, diagnosing, and retrofitting the building's energy performance in the operation and maintenance phase of the building sector, which aims to reflect the unexpected changes in the climate and energy environments as well as in the energy policies and technologies under the new paradigm of an "*Urban Organism*".

1.2. Outline

In Section 2, the three phases of monitoring, diagnosing, and retrofitting are established to continuously manage the building's

[1] For interpretation of color in Fig. 2, the reader is referred to the web version of this article.

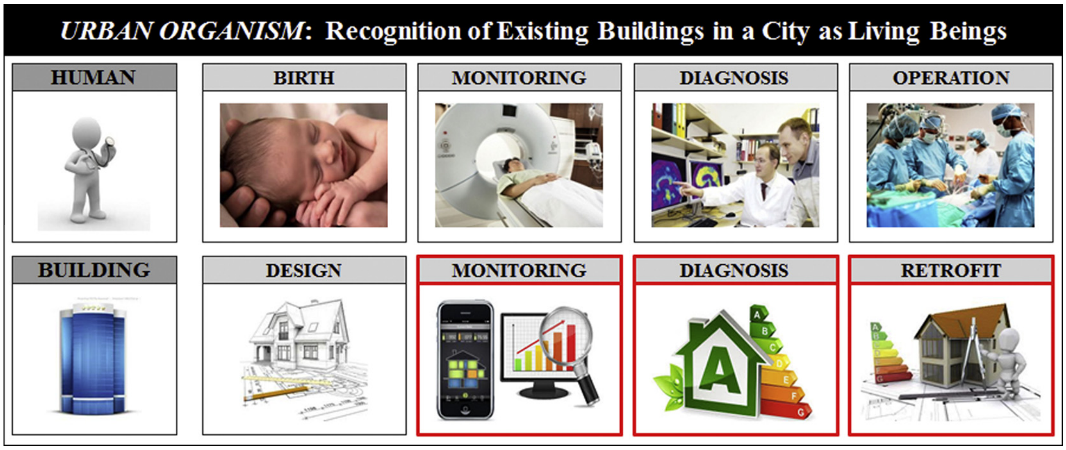

Fig. 2. Recognition of existing buildings in a city as living beings.

dynamic energy performance in the operation and maintenance phase. Also, this study defines the objective, potential activities, and applicable information technologies by phase.

In Section 3, an extensive literature review is conducted to explore the concept of the monitoring phase for a building's dynamic energy performance. Particularly, the geographic information system (GIS), the light detection and ranging (LiDAR) data, and the infrared thermography (IRT) method are thoroughly reviewed.

In Section 4, an extensive literature review is conducted to explore the concept of the diagnosing phase for a building's dynamic energy performance. Particularly, the asset rating system (referred to as an estimation method) and the operational rating system (referred to as a measurement method) are thoroughly reviewed.

In Section 5, an extensive literature review is conducted to explore the concept of the retrofitting phase for a building's dynamic energy performance. Particularly, the energy-saving techniques (e.g., the passive and active design techniques) and the new and renewable energy systems (e.g., the photovoltaic energy, solar thermal energy, geothermal, and fuel cell systems) are thoroughly reviewed.

In Section 6, the various illustrative examples of the monitoring, diagnosing, and retrofitting of a building's dynamic energy performance are provided.

In Section 7, the future directions are suggested for overcoming the possible challenges and for investigating the potential opportunities in sustainable construction management strategies for monitoring, diagnosing, and retrofitting the building's dynamic energy performance in the operation and maintenance phase of the building sector.

2. Major phases of a building's dynamic energy performance management

In general, the energy consumption in the operation and maintenance phase of the building sector accounts for a large portion of the total energy consumption from the life cycle perspective. This is the reason why the sustainable construction management strategies should be established to control the building's dynamic energy performance by reflecting the unexpected conditions in the urban-based built environments. Based on the study of Koo [11], this study subdivides the major phases of a building's dynamic energy performance management into three phases: the monitoring, diagnosing, and retrofitting phases. Table 1 shows the three major phases of a building's dynamic energy performance management and the associated potential activities in each phase. Ultimately, the three major phases should be integrated into a system (i.e., a carbon-integrated management system as a large complex system) that is appropriate for the urban-based built environments, which allows to achieve the energy-efficient and low-emission buildings from the perspective of the holistic approach.

Table 1
Major phases for the building's dynamic energy performance management.

Phase	Potential activities
Monitoring	• Data collection (e.g., physical information of the building, utilization information of the building, geographical and meteorological information) • Data analysis (e.g., analysis of the energy demand and supply, and energy self-sufficiency rate, and geostatistical analysis of the regional distribution) • GIS and IRT method can be used to monitor the building's dynamic energy performance
Diagnosing	• Asset rating system (referred to as an estimation method) that is mainly used in the design phase of new buildings • Operational rating system (referred to as a measurement method) that is mainly used in the operation and maintenance phase of existing buildings • It is required to consider the performance gap between the asset rating and the operational rating in advance
Retrofitting	• Establishment of applicable energy retrofit strategy using ESTs and NREs • Energy simulation using the typical tools (e.g., EnergyPlus, TRNSYS) • Life cycle economic and environmental assessment using the life cycle cost analysis and life cycle assessment • Definition of the multi-objective optimization using the simplified equation based on the several optimization algorithms (e.g., genetic algorithm, harmony search, etc.)

- *Phase 1 (Monitoring)*: In this phase, for monitoring a building's dynamic energy performance, the physical, utilization, and geographical and meteorological information of the building should be collected. Also, the energy demand and supply and the energy self-sufficiency rate can be analyzed using the collected data. Finally, geostatistical analysis of the regional distribution can be conducted using GIS tools such as ArcGIS and the IRT method.
- *Phase 2 (Diagnosing)*: In this phase, for diagnosing a building's dynamic energy performance, the following two types of energy performance rating system should be analyzed: (i) the asset rating system (referred to as an estimation or calculation method);

and (ii) the operational rating system (referred to as a measurement method). Also, additional strategies should be considered to overcome the performance gap between the asset rating system (which is mainly used in the design phase of new buildings) and the operational rating system (which is mainly used in the operation and maintenance phase of existing buildings).

- *Phase 3 (Retrofitting)*: In this phase, for retrofitting a building's dynamic energy performance, applicable energy retrofit strategies using the combination of energy-saving techniques (ESTs) and new and renewable energies (NREs) should be established. Energy simulation can be conducted using the typical tools, such as EnergyPlus and TRNSYS, from which the potential energy savings can be analyzed. For each of the energy retrofit strategies, life cycle economic and environmental analysis can be conducted. Finally, according to the indexes selected by the final decision-maker (e.g., initial investment cost, net present value, saving-to-investment ratio, etc.), the optimal energy retrofit strategy can be determined based on the concept of multi-objective optimization.

3. Monitoring phase of a building's dynamic energy performance

The previous studies for a building's dynamic energy performance were conducted using the GIS, the LiDAR data, and the IRT method.

First, from the macro point of view (city district scale), the dynamic energy performance was monitored using GIS and LiDAR data. The GIS can be used for collecting, storing, assessing, and visualizing all spatial data, such as geometry data (e.g., coordinate information, topological information, etc.) and attribute data (e.g., energy performance, renewable energy potential, CO_2 emission, etc.) [21–24]. Also, the LiDAR is an effective remote sensing tool for measuring a three-dimensional coordinate by emitting a short laser pulse to the target object and analyzing the reflected light [25–28].

Second, from the micro point of view (building scale), the dynamic energy performance was monitored using the IRT method. The infrared camera is equipment used for establishing images of the thermal distribution of a building by detecting the infrared radiation emitted from the target object, which can be used to measure the surface temperature of building envelopes [29–32].

3.1. Macroscopic monitoring using GIS and LiDAR data

From the macro point of view (city district scale), the previous studies were conducted to monitor a building's dynamic energy performance in terms of two aspects: (i) monitoring the building energy consumption; and (ii) monitoring the building energy generation.

3.1.1. Monitoring the building energy consumption

Many previous studies were conducted to monitor a building's energy consumption (e.g., electricity, gas energy, etc.) for evaluating the building's dynamic energy performance using GIS and LiDAR data (refer to Table 2) [25,33–40].

- *Monitoring the building energy consumption using GIS:* The previous studies developed monitoring methods of the building energy consumption using GIS [33–38]. Dall'O' et al. [33] developed a method for monitoring a building's dynamic energy performance by integrating the information on the building stack (e.g., cartographic documentation, thematic map, geometric data, etc.) and energy audits (e.g., winter heating, solar photovoltaic (PV) system, etc.) based on the GIS platform in Basel. Howard et al. [34] developed a model for estimating the building energy use intensity using GIS and robust multiple linear regression in New York City. The model assumed that a building's energy consumption depends on the building type (e.g., residential building, educational building, office building, etc.). Using the developed model, various maps of the annual energy consumption (e.g., space cooling, water heating, base electric, space heating, etc.) were proposed. Meanwhile, Fabbri et al. [37] and Hoesen et al. [38] developed a method for monitoring the energy performance of historical buildings. Fabbri et al. [37] proposed the use of the zone energy indicator (the ratio between the energy consumption and the number of urban units) to analyze the distribution of the environmental energy performance of the heritage buildings in Ferrara city. It was found that the zone energy indicator of the old town (28.45 MW h/UI) was higher than that of all the towns (49.75 MW h/UI). Hoesen et al. [38] evaluated the building stock ages for reducing the energy consumption of historical buildings. A total of 1091 buildings in Vermont completed from 1885 to 1940 were digitized using the GIS-based approach and historical parcel data. It was found that the thermal efficiency of the oldest 1091 buildings should be improved to minimize the buildings' fuel consumption and to reduce their GHG emissions.
- *Monitoring the building energy consumption using LiDAR data:* The previous studies were conducted to develop monitoring methods of a building's energy consumption using LiDAR data [25,39]. Tooke et al. [25] presented a novel method that combined with the building energy parameters (e.g., envelope resistivity, air leakage, and solar gains) and LiDAR data (e.g., volume, roof area, and wall area) to estimate the residential-building thermal-energy demand in Vancouver. In this study, the correlation between a building's morphological characteristics and the age of the house and the correlation between the local environment and energy performance were determined. Further, the spatial distribution of the energy demand in a city was analyzed. Christen et al. [39] validated the estimated CO_2 emissions from an urban neighborhood through eddy-covariance measurements. This study integrated the LiDAR data (e.g., surface cover factions, building dimensions, building form, etc.) with building energy consumption data, and evaluated the CO_2 emissions due to several factors (e.g., building, transportation, human respiration, vegetation, and soil). It was found that there were significant seasonal and weekday–weekend differences between the estimated and measured CO_2 emissions.
- *Monitoring the building energy consumption using both GIS and LiDAR data:* Compared to the previous studies that used only the GIS method, the previous studies that used both the GIS and LiDAR data could analyze the correlation between a building's physical information and energy consumption. Ko et al. [40] developed a statistical model for estimating the space cooling energy use using GIS and LiDAR data in a residential home. This study established four types of variables (i.e., summer cooling energy use, occupant behavior, property condition, and demographic and socioeconomic status) as well as the urban form (e.g., land cover and vegetalization) data extracted from LiDAR data. As a result, it was determined that the higher the population density, green space density, and vegetation density are, the lower the summer cooling energy use is.

3.1.2. Monitoring the building energy generation

Many previous studies were conducted to monitor the various factors (e.g., rooftop space, solar radiation, etc.) related to the building's energy generation, using GIS and LiDAR data (refer to Table 3) [12,18,41–51].

Table 2
Literature review on the macroscopic monitoring using GIS and LiDAR data (focused on building energy consumption monitoring).

Methods	Authors	Monitoring	Input data	Software	Countries	Main findings
GIS	Dall'O' et al. [33]	Energy performance classification	• Total 26 databases (Construction period, Façade maintenance status, Fenestration maintenance status, Roof type, Roof orientation, etc.)	Arcview	Lombardy region (Italy)	• The data on building information and energy audit can be integrated with low cost using the proposed method and map based on GIS platform • The owner and local administrators can monitor the energy efficiency of buildings
	Howard et al. [34]	Energy end-use intensity	• Annual energy consumption (e.g. electricity, natural gas, steam, or fuel oil) and information about the building stock	N/A	New York (US)	• The various maps of the annual energy consumption by block area were proposed • Most of the energy is consumed for space and domestic hot water in the residential building
	Yeo et al. [35]	Urban climate and energy	• Ratio of land cover area, building information, and geography view factors	N/A	Gwang-myung/Si-heung (South Korea)	• The environment and energy geographical information (E-GIS) construction model was developed to reduce urban energy use by integrating urban GIS integration model, E-GIS DB model, and visualization model
	Ascione et al. [36]	Energy performance of buildings and districts	• Energy audit, ISTAT census, Sector's study, literature data, ENEA database, Sector standards, and digital cartographic base	N/A	Benevento (Italy)	• The new analytical methodology was developed to evaluate the energy demand of existing and new buildings • The urban energy map can visualized the energy performances and criticalities in city districts
	Fabbri et al. [37]	Energy performance in heritage buildings	• Italian real estate information based on ISTAT Census 2001 and SACE (System for energy performance certification accreditation) database	ArcGIS	Ferrara (Italy)	• The energy performance in city, town, or district can be evaluated through the energy map project based on GIS provides • The ZEI of the old town (28.45 MW h/UI) is higher than the ZEI of the all town (49.75 MW h/UI).
	Hoesen et al. [38]	Improve thermal efficiency in historical buildings	• Building outlines, location of windows and doors, widths of the street and sidewalk, construction materials and building purpose	ArcGIS	Poultney (US)	• The total 1091 structures during 1885–1940 in Vermont were digitized using GIS-based approach and historical parcel data • The oldest buildings (total 1091 structures) built in prior to 1941 were needed to improve the thermal efficiency for minimizing fuel consumption and reducing GHG emissions
LiDAR data	Tooke et al. [25]	Thermal energy demand	• Natural Resources Canada's ecoENERGY retrofit program, Municipal cadastral libraries, 2011 Canadian national census data, BC Assessment, iHMP-35A, and Kipp & Zonen CNR-1	Leica ALS60 & HOT 2000	Vancouver (Canada)	• The LiDAR data (e.g., volume, roof area and wall area) were combined with the building energy parameters (e.g., envelope resistivity, air leakage, and solar gains) • The relation analysis between two variables (building's morphological characteristics & age of the house and local environment and energy performance) was conducted using integrated data set
	Christen et al. [39]	Carbon-dioxide emission	• Surface cover factions, building dimensions, building form, building volume, vegetation characteristics, and building energy consumption	HOT2000 & OEE Screening tool	Vancouver (Canada)	• The annual difference between modeled and measured CO_2 emissions was 11% • The error rate between the modeled and measured CO_2 emission in summer have lower than in winter
GIS & LiDAR data	Ko et al. [40]	Evaluation of the association between urban form and residential energy use	• 2008 Sacramento Municipal Utility District, 2010 Census data, and Tax assessor data, and LiDAR data and GIS	Stata	Sacramento (US)	• The LiDAR data (e.g., land cover and vegetation) were combined with the four types of variables (summer cooling energy use, occupant behavior, property condition, etc.) • Higher population density, green space density, and vegetation rate, less use of summer cooling energy

Table 3
Literature review on the macroscopic monitoring using GIS and LiDAR data (focused on building energy generation monitoring).

Methods	Authors	Monitoring	Input data	Software	Countries	Main findings
GIS	Koo et al. [41]	Monthly average daily solar radiation	• Geographic data (e.g., latitude, longitude, etc.) and meteorological (e.g., altitude, monthly mean percentage of sunshine, etc.) data	ArcGIS	South Korea	• The monthly average daily solar radiation estimation model was developed using GIS and advanced CBR • The estimation accuracy and standard deviation of proposed model were 95.69% and 3.67%
	Lee et al. [42]	Monthly average daily solar radiation	• Geographic data (e.g., latitude, longitude, etc.) and meteorological (e.g., altitude, monthly mean percentage of sunshine, etc.) data	ArcGIS	South Korea	• The monthly average daily solar radiation estimation model was developed using advanced CBR and geostatistical technique • The mean absolute percentage error between the measured and estimated MADSR in Daegu, in South Korea was 4.05%
	Hong et al. [18]	Electric generation of the rooftop PV system	• Geographical information (e.g., latitude, etc.), meteorological information (e.g., monthly average daily solar radiation, etc.), and on-site installation (e.g., the azimuth of the installed panel, etc.)	ArcGIS	South Korea	• The sensitivity analysis results shows that there is a difference of annual electricity generation of the rooftop PV system by impact factors (regional factor: 1.12-fold, azimuth of the installed panel: 1.62-fold, and slope of the installed panel: 1.37-fold)
	Koo et al. [12]	Potential of the rooftop PV system	• Physical, utilization, and geographical information on the building, physical information on the solar PV panel, and regional meteorological and geographical information	ArcGIS	South Korea	• The potential of the net-zero energy solar building was analyzed by regions and shows a broad spectrum of roughly 30–250% • The energy consumption per roof area largely affects the potential of the net-zero energy solar building
	Gastli et al. [45]	Solar electricity prospects	• Geographic (e.g., site latitude, elevation, etc.) and topographic (e.g., effects of shadows) information	ArcMap	Oman	• The solar electricity prospect in Oman is positive, because of high potential of solar energy and solar generation
	Esclapés et al. [46]	Adaptability of photovoltaic energy	• Cadastral cartography and solar radiation data	gvSIG package	Spain	• The GIS-based method can provide the 3D cartography data (e.g., solar irradiance, orientation, potential of PV system, etc.) for the urban facades
LiDAR data	Lukač et al. [47]	Building roofs photovoltaic potential	• Spatial data (e.g., inclination, orientation, spatio-temporal self-shadowing, etc.) from aerial LiDAR scanning	N/A	Slovenia	• The proposed method was developed by considering the nonlinear efficiency characteristics of PV module, inverter, and so on • The proposed method shows the high estimation accuracy compared with the measured electrical power
	Redweik et al. [48]	Solar energy potential on roof and facades	• LiDAR data (e.g., building information, tree canopy, etc.) and SOLTERM database (i.e., hourly mean values for horizontal direct and diffuse irradiation)	N/A	Lisbon	• The 3D solar urban model was developed to estimate the solar energy potential using LiDAR data, astronomical model, and radiation model • The annual irradiation on roof is higher than vertical façade
	Lukač et al. [49]	Solar potential and suitability for PV system	• Lidar data, digital surface model data, pyranometer data, and leaf area index data	N/A	Slovenia	• The new method based on LiDAR data estimated and rated the solar potential and suitability for PV system • The estimated and measured solar radiation has a high correlation
GIS & LiDAR data	Kodysh et al. [50]	Solar potential	• Lidar data (e.g., vegetation, buildings, etc.) and solar radiation data	ArcGIS	Tennessee	• The proposed method was developed by combining the LiDAR data with upward-looking hemispherical viewshed algorithm • The estimation accuracy using proposed method is higher than the simple method
	Santos et al. [51]	PV potential	• Planimetric data (e.g., building foot print, the census block groups, and the land use map) and altimetric data (e.g., height information of the all element above the terrain)	ArcGIS & PVGIS	Lisbon	• PV potential of residential building was evaluated using GIS and LiDAR data • The 25% of the electricity demand in study area can be met through electricity generation of rooftop PV system

- *Monitoring the building energy generation using GIS:* The previous studies developed monitoring methods for the various factors on the building energy generation, using GIS data [12,41–46]. Koo et al. [41] developed an estimation model of the monthly average daily solar radiation (MADSR) using GIS data and advanced case-based reasoning (A-CBR). The A-CBR method was used for estimating the MADSR at an unmeasured location and the GIS was used for visualizing the estimated MADSR. In this study, the geographic data (e.g., latitude, longitude, etc.) and meteorological data (e.g., monthly mean percentage of sunshine, monthly mean cloud amount, etc.) in South Korea were collected. The estimation accuracy and standard deviation of the proposed model were determined to be 95.69% and 3.67%, respectively. Lee et al. [42] developed the map of the MADSR in South Korea using the A-CBR and kriging methods (i.e., one of the geostatistical techniques). In this study, the MADSR was estimated at an unmeasured location using the A-CBR method. The mean absolute percentage error between the measured and estimated MADSR was determined to be 4.05%. Koo et al. [12] analyzed the potential of the rooftop PV system to achieve the net-zero energy solar buildings (nZESB). Several data (e.g., physical, utilization, and geographic information of the building, physical information of the solar PV panel, etc.) were also collected. The study provided the energy self-sufficiency rate of buildings by region, and visualized such data using GIS. As a result, the potential of nZESB showed a broad spectrum of roughly 30–250%. Also, it was determined that the energy consumption per roof area largely affects the potential of nZESB.

- *Monitoring the building energy generation using LiDAR data:* The previous studies developed the monitoring methods of the various factors on the building energy generation using LiDAR data [47–49]. Lukač et al. [47] estimated the PV potential of buildings' roofs using LiDAR data. The proposed method considers the nonlinear efficiency characteristics of the PV module, inverter, and long-term solar irradiance measurements. Three types of PV module (i.e., amorphous silicon, polycrystalline silicon, and monocrystalline silicon) were considered to estimate the PV potential of buildings' roofs. As a result, the proposed method shows high estimation accuracy compared with the measured electrical power. Redweik et al. [48] assessed the solar energy potential of roofs and the vertical façade using LiDAR data. This study considered three factors (i.e., ground, building, and trees) affecting the solar radiation using airborne LiDAR data. It was found that the annual irradiation on the roof is higher than that on the vertical façade.
- *Monitoring the building energy generation using both GIS and LiDAR data:* The previous studies developed monitoring methods of the various factors on the building energy generation using both GIS and LiDAR data [50,51]. Kodysh et al. [50] estimated the solar potential of multiple building roofs by combining the LiDAR-data-based digital elevation model (DEM) with the upward-looking hemispherical viewshed algorithm. This study considered the unique characteristics of the building roof using LiDAR-data-based DEM, and calculated the solar radiation for the specific location using the upward-looking hemispherical viewshed algorithm. It was found that the proposed method has higher estimation accuracy than the simple method. This is because the proposed method can consider the building characteristics and the shading effect in a more detailed manner.

3.2. Microscopic monitoring using IRT method

From the micro point of view (building scale), the building envelop (e.g., windows, doors, walls, etc.) should be monitored when evaluating the building's dynamic energy performance. The influence factors of a building's dynamic energy performance can be divided into four categories: (i) thermal transmittance and heat transfer coefficient; (ii) sensible heat release; (iii) thermal bridges; and (iv) air temperature (refer to Table 4) [57–67].

- *Thermal transmittance and heat transfer coefficient:* Albatici et al. [57], Fokaides et al. [58], and Ohlsson et al. [59] developed methods of evaluating the thermal transmittance and heat transfer coefficient using the IRT method. Albatici et al. [57] developed a robust procedure for evaluating the thermal transmittance of opaque elements using the infrared thermovision technique. It was determined that the thermal transmittance of a brick (heavy) structure can be more accurately measured than that of a timber (light) structure. Fokaides et al. [58] measured the overall heat coefficient (*U*-value) by building element (e.g., wall, roof, and glazing) using the IRT method. This study calculated the percentage absolute deviation between the notional and the measured *U*-value using the IRT method, resulting in the range of 10–20%. Also, though sensitivity analysis, it was determined that the most sensitive variable is the reflected apparent temperature and emissivity of the building surface.
- *Sensible heat release:* Sham et al. [60,61] developed the continuous surface temperature monitoring (CSTM) method for evaluating the nocturnal sensible heat release by building fabrics using the IRT method. The CSTM could be simultaneously applied to several buildings to evaluate the nocturnal sensible heat release. Through a case study, it was proven that the granite walls release more sensible heat than the ceramic walls.
- *Thermal bridge:* Asdrubali et al. [62], Bianchi et al. [63], and Zalewski et al. [64] developed methods of evaluating the thermal bridge using the IRT method. Asdrubali et al. [62] analyzed several types of thermal bridges using simple thermographic surveys and the subsequent analytical processing. The validation process was conducted using a heat flow meter and numerical analysis (computational fluid dynamic analysis). Bianchi et al. [63] collected continuous monitoring data (e.g., indoor air temperature, surface temperature, and thermal fluxes) to estimate the overall effect of a total of nine thermal bridge typologies. Compared with the energy consumption without a thermal bridge, the energy consumption with a thermal bridge was increased by about 9%.
- *Air temperature:* Porras-Amores et al. [65], Cehlin et al. [66], and Djupkep et al. [67] described IRT as a valuable method of measuring the air condition (e.g., air temperature, air speed, etc.). Porras-Amores et al. [64] proposed a monitoring screen system that makes use of aluminum paper and rigid plastic. The proposed monitoring screen system was used to conduct the precise measurement of the indoor air temperature, and its performance was verified by comparing the measurements provided by the IRT and the temperature sensors. The limitations of the indoor air temperature measurements (e.g., emissivity, camera calibration, poor focus, etc.) were overcome by using the proposed monitoring screen system. Cehlin et al. [66] proposed visualization and measurement techniques for measuring the air temperature close to a low-velocity diffuser by using the IRT method and a measuring screen. The influence parameter and error were analyzed to improve the accuracy of the proposed technique. As a result, it was determined that it is important to select the appropriate screen material with low emissivity to reduce the measuring error.

4. Diagnosing phase of a building's dynamic energy performance

This study reviewed the previous studies on the diagnosing phase of a building's dynamic energy performance in terms of two categories: (i) asset rating (i.e., based on the predicted energy use) and (ii) operational rating (i.e., based on the measured energy use). Within these two categories, various studies have been conducted.

4.1. Asset rating system

Asset rating is an index for estimating and evaluating the potential energy performance of a building considering the building's physical characteristics, such as its exterior performance and HVAC (heating, ventilating, and air-conditioning) system. For the application of the asset rating to the diagnosis of a building's dynamic energy performance, the followings should be considered: (i) it is based on the predicted energy usage; (ii) it is used in the design phase of a building; (iii) it is used in new buildings where there is no measured energy usage; and (iv) it is based on the building's energy demand. Therefore, the asset rating cannot provide any information related to the building's operation and

Table 4
Literature review on the microscopic monitoring using IRT method.

Monitoring	Author	Infrared (IR) cameras	Methods	Main findings
Thermal transmittance & Heat transfer coefficient	Albatici et al. [57]	• IR resolution: 320 × 240 pixels • Thermal sensitivity: 0.1 °C • Wavelength range: 8–14 μm	• Infrared thermovision technique, International standard approach, and heat flow meter (HFM)	• Compared with the timber (light) structure, the measurement for the brick (heavy) structure is more accurate • The lighter structure, the higher sensitivity
	Fokaides et al. [58]	• IR resolution: 320 × 240 pixels • Thermal sensitivity: 50 mk • Wavelength range: 7.5–13 μm	• Infrared thermography (IRT) • European Standard EN1560 • Heat flux meters (HFM) • Sensitivity analysis	• The percentage absolute deviation between the notional and the measured U-Value for IRT was calculated to be of 10–20% • Most sensitive variable were determined the reflected apparent temperature and emissivity of the buildings surface though the sensitivity analysis
	Ohlsson et al. [59]	• IR resolution: 160 × 120 pixels • Thermal sensitivity: ⩽0.08 K • Wavelength range: 8–14 μm	• Infrared thermography (IRT) • Heat flow meter (HFM)	• The proposed method has several functions such as simultaneous measurement of surface temperature, surrounding radiative temperature, and air temperatures • There was a 2.6 W/m^2 different between IRT and HFM
Sensible heat release	Sham et al. [60]	• IR resolution: 320 × 240 pixels • Thermal sensitivity: 0.08 °C • Wavelength range: 8–14 μm	• Traditional internal energy equation (IE method) • Continuous surface temperature monitoring (CSTM) technique	• The CSTM could be applied on lots of buildings simultaneously to evaluate the nocturnal SH release • The building with granite wall released the highest SH (2.65 MJ/m^2) and the ceramic tile wall released the lowest SH (1.26 MJ/m^2)
	Sham et al. [61]	• IR resolution: 320 × 240 pixels • Thermal sensitivity: 0.08 °C • Wavelength range: 8–14 μm	• Continuous surface temperature monitoring (CSTM) technique	• There are no significant difference between buildings of different sizes and colors • There are significant differences between buildings with different fabrics in hot and cold seasons
Thermal bridges	Asdrubali et al. [62]	• Resolution: 320 × 240 pixels • Wavelength: 7.5–13.0 μm	• Simple thermographic surveys • Subsequent analytical processing • Heat flow meter • Numerical analysis (CFD analysis)	• The simple thermographic surveys and subsequent analytical processing were conducted to evaluate the several type of thermal bridge • The heat flow meter and numerical analysis were conducted to validate the proposed methods
	Bianchi et al. [63]	N/A	• Infrared thermography (IRT) • Proposed quantitative method	• The proposed method was presented the reliable tool to quantify the thermal bridges • Compared with energy consumption without thermal bridge, energy consumption with thermal bridge was increased about 9%
	Zalewski et al. [64]	• IR resolution: 320 × 240 pixels	• Infrared thermography (IRT) • Heat flux meter • Numerical predictions	• Thermal bridge can be identified using IRT • The thermal performance can be calculated using numerical prediction • The proposed method can be used to consider the several alternatives for wall in insulations.
Air temperature	Porras-Amores et al. [65]	• Resolution: 320 × 240 pixels • Thermal sensitivity: 50 mK • Wavelength: 7–13 μm	• Infrared thermography (IRT)	• The proposed method allows the precise measurement of the indoor air temperature • The limitations of the indoor air temperature measurements were overcome by proposed monitoring screen system
	Cehlin et al. [66]	N/A	• Infrared thermography (IRT)	• The influence parameter and error were analyzed to improve the accuracy of the proposed technique • It is important to select appropriate screen material with low emissivity to reduce measuring error
	Djupkep et al. [67]	• Resolution: 384 × 288 pixels • Wavelength: 7.5–14.0 μm	• Infrared thermography (IRT) • Numerical experiment	• The 2D and 3D visualization of air condition can be possible using IRT • The proposed method using IRT has proved that has a good performance by validating using numerical experiment

occupants. There are some examples such as the home energy rating system (HERS) in the United States (USA) and the energy performance certificates (EPCs) in the United Kingdom (UK) [68–70].

Based on the asset rating, previous studies have been conducted to diagnose a building's dynamic energy performance, as follows: (i) predicting a building's dynamic energy performance; and (ii) developing an asset rating model.

4.1.1. Predicting a building's dynamic energy performance

Many previous studies predicted a building's dynamic energy performance using various approaches, such as the engineering, statistical, and hybrid approaches (refer to Table 5) [71–97]. Based on the results of the approach used, a building's dynamic energy performance can be diagnosed.

Table 5
Literature review on the predicting a building's dynamic energy performance.

Approach		Authors	Methodology	Target	Building type	Location
Engineering approach	Equation	Lu et al. [76]	• Energy balance equations	• Indoor air temperature, Energy consumption	Commercial	Finland
	Simulation	Fumo et al. [77]	• EnergyPlus	• Electricity consumption, Gas consumption	Office	US
Statistical approach	Regression analysis	Catalina et al. [78]	• Regression analysis	• Heating demand	Residential	France
		Wang [79]	• Regression analysis	• Annual energy consumption, Energy use intensity (EUI)	Hotel	Taiwan
		Catalina et al. [80]	• Regression analysis	• Heating demand	Residential	Romania
		Aydinalp-Koksal and Ugursal [81]	• Conditional demand analysis (CDA)	• Energy consumption	Residential	Canada
	Neural network	Ekici and Aksoy [82]	• Artificial neural network (ANN)	• Heating energy	–	Turkey
		Wong et al. [83]	• Artificial neural network (ANN)	• Electricity consumption	Office	Hong Kong
		Escrivá-Escrivá et al. [84]	• Artificial neural network (ANN)	• Electricity consumption	Educational	Spain
	Support vector machine	Li et al. [85]	• Support vector machine (SVM)	• Hourly cooling load	Office	China
		Jain et al. [86]	• Support vector regression (SVR)	• Electricity consumption	Multi-family residential	US
	Methodology integration	Li and Su [87]	• Hybrid genetic algorithm hierarchical adaptive network-based fuzzy inference system (GA-HANFIS)	• Daily air conditioning consumption	Commercial	China
		Li et al. [88]	• Hybrid genetic algorithm-adaptive network-based fuzzy inference system (GA–ANFIS)	• Energy consumption	Library	China
		Wang and Meng [89]	• Artificial neural network (ANN), Autoregressive integrated moving average (ARIMA)	• Energy consumption	–	China
	Others	Yu et al. [90]	• Decision tree	• Energy use intensity (EUI)	Residential	Japan
		Tsanas and Xifara [91]	• Iteratively reweighted least squares, Random forests	• Heating load, cooling load	Residential	Greece
		Koo et al. [92]	• Four-node-based Lagrangian finite element	• Heating demand, cooling demand	Residential	South Korea
		Seo et al. [93]	• Nine-node-based Lagrangian finite element	• Heating demand, cooling demand	Residential	South Korea
	Comparison between various methodology	Tso and Yau [94]	• Regression analysis, Decision tree, Neural networks	• Electricity consumption	Residential	Hong Kong
		Neto and Fiorelli [95]	• EnergyPlus, artificial neural network (ANN)	• Energy consumption	School	Brazil
Hybrid approach		Wang and Xu [96]	• Frequency response characteristic, Genetic algorithm (GA)	• Cooling load	Office	Hong Kong
		Xu et al. [97]	• EnergyPlus, ANN, Affiliation network	• Energy consumption	Residential	US

- *Engineering approach:* It uses physical principles to predict a building's dynamic energy performance. This can be done in two different ways: (i) by calculating the theoretical energy performance of the building using equations; and (ii) by calculating the theoretical energy performance of the building using simulation tools such as EnergyPlus, DesignBuilder, TRNSYS, eQUEST, and ESP-*r*. Lu et al. [76] developed a physical model using energy balance equations to accurately predict the indoor air temperature and energy consumption. This study applied the open- and closed-loop system approaches, the Laplace transform, and singular-value decomposition to accurately reflect the dynamics of a building's thermal performance, and their uncertainties. The results showed that the model complexity and the model parameters were minimized while still providing high accuracy. Fumo et al. [77] developed the benchmark models using the EnergyPlus software to obtain predetermined coefficients that can be used for predicting the dynamic energy performance of office buildings in the U.S. The results showed that the errors obtained with regard to the estimated energy consumption were mainly within 10%.
- *Statistical approach:* It uses historical or simulated energy use data to predict a building's energy dynamic performance. This can be done in numerous ways, such as through the regression analysis, the neural networks, the support vectors machine, the fuzzy theory, the genetic algorithm, the decision tree, and the finite-element method. First, many studies predicted a building's dynamic energy performance using regression analysis, neural networks, and the support vectors machine, which are the three most common statistical approaches for energy prediction [78–86]. Wongetal. [83] used an artificial neural network (ANN) for predicting the dynamic energy performance of office buildings in Hong Kong. As a result, the Nash–Sutcliffe Efficiency Coefficient, a measure for the predictive power of the ANN model, was determined to be 0.996 for total building electricity use, which indicated great predictive performance. Second, some studies integrated more than two statistical approaches to predict a building's dynamic energy performance [87–89]. Li et al. [88] integrated the fuzzy theory and genetic algorithm and developed a hybrid genetic algorithm–adaptive network-based fuzzy inference system (GA–ANFIS) for predicting the dynamic energy performance of library buildings in China. The results showed that the hybrid GA–ANFIS model has a higher prediction performance than the ANN model. Third, less common methods, such as the decision tree and the finite-element method, were used in some recent studies [90–93]. Seo et al. [93] developed a nine-node-based Lagrangian finite-element model for estimating the heating and cooling demand of residential buildings with different

building envelope designs in South Korea. By comparing the root mean square error, mean absolute error, and mean absolute percentage error of the proposed and previous models, it was shown that the prediction performance of the nine-node-based model was improved compared to that of the four-node-based model.

- *Hybrid approach:* It uses both physical principles and historical energy use data to predict a building's dynamic energy performance. Xu et al. [97] integrated the engineering approach (i.e., simulation with the EnergyPlus software) with the statistical approach (i.e., ANN) to develop a holistic model that can consider the influence of buildings, residents, and the neighborhood context for predicting the dynamic energy performance of residential buildings in the U.S. The results showed that eco-feedback systems using place-based social networks can provide improvements in energy performance at the inter-building level.

4.1.2. Developing the asset rating model

Other previous studies developed an asset rating model for diagnosing a building's dynamic energy performance using various approaches, such as the calculation, simulation, and statistical approaches (refer to Table 6) [98–103].

- *Calculation approach:* Ballarini and Corrado [98] used a calculation approach based on energy balance equations to develop an asset rating model for the residential buildings in Italy. This kind of method, however, requires a considerable number of input data in the calculation, which makes it difficult to develop the asset rating in an accurate way.
- *Simulation approach:* Pernigotto et al. [99], Mills et al. [100], and Daniel et al. [101] used a simulation approach to develop a more reliable asset rating model, by considering the actual building conditions. Pernigotto et al. [99] compared the multi-year weather data with the reference year weather data to evaluate a building's dynamic energy performance for five northern Italy locations, using the TRNSYS software. The results showed that the specific reference year data should be used to accurately evaluate the energy demand and asset rating of a building's dynamic energy performance in the case of a low number of historic weather data and climates with large variability, such as Italy. Daniel et al. [101] considered the occupant behaviors in a low-energy house for predicting the house energy rating using the AccuRate simulation program in Australia. The results showed that the current occupant assumptions overestimated the energy consumption in low-energy dwellings, which made it difficult to appropriately reflect the actual heating and cooling loads.
- *Statistical approach:* Reilly et al. [102] and Melo et al. [103] used a statistical approach to develop a simple asset rating model while still providing high accuracy. Reilly et al. [102] conducted sensitivity and Monte Carlo analyses to reduce the input data requirements of the baseline model, which fully adopted the Dwelling Energy Assessment Procedure and the Standard Assessment Procedure methodology for developing a simplified residential energy asset rating model. The results showed that it could maintain high accuracy (95%) with fewer variables than the baseline model. Melo et al. [103] used the ANN model to improve the accuracy of the surrogate models for building shell energy labeling in Brazil. A total of 3200 building energy consumption data from the EnergyPlus software were used to develop the ANN model. The results showed that the ANN model could be successfully applied to the surrogate models for building shell energy labeling with 16% errors for a 90% confidence level.

4.2. Operational rating system

Operational rating is an index for comparing and assessing the actual energy performance of a building considering the building's energy consumption data. For the application of the operational rating to the diagnosis of a building's dynamic energy performance, it is necessary to consider the following: (i) it is based on the measured energy consumption; (ii) it is used in the operational and maintenance phase of a building; (iii) it is used in existing buildings where there are measured energy consumption data; and (iv) it is based on the building energy consumption. Therefore, the operational rating can provide information not only about a building's physical characteristics but also about the building's operation and occupants. For example, there are ENERGY STAR in the U.S. and the display energy certificates (DECs) in the UK [68–70].

Based on the operational rating, previous studies have been conducted to diagnose a building's dynamic energy performance, as follows: (i) benchmarking a building's dynamic energy performance; and (ii) developing an operational rating model.

4.2.1. Benchmarking a building's dynamic energy performance

Many previous studies established benchmarking models for diagnosing a building's dynamic energy performance using various approaches, such as the engineering, statistical, and hybrid approaches (refer to Table 7) [70,104–123].

- *Engineering approach:* It compares the measured energy consumption data with the theoretical value from physical principles to benchmark a building's dynamic energy performance [106]. This can be done in two different ways: (i) by calculating the theoretical energy performance of a building using equations; and (ii) by calculating the theoretical energy performance of a building with simulation tools. Burman et al. [107] used the building physics method (i.e., UK National Calculation Methodology (NCM)) and aggregated end-use (i.e., the Technical Memorandum 22 (TM22) methodology) to develop a benchmarking model for diagnosing the dynamic energy performance of school buildings in the UK. The results showed that the energy benchmarks derived from the proposed method could be used as the baselines for diagnosing a building's dynamic energy performance, but it might not be practical for all buildings due to its complexity.

Table 6
Literature review on the developing the asset rating model.

Approach	Authors	Methodology	Target	Building type	Location
Calculation approach	Ballarini and Corrado [98]	• Energy balance equations	• Primary energy rating	Residential	Italy
Simulation approach	Pernigotto et al. [99]	• TRNSYS	• Heating demand, cooling demand	Residential	Italy
	Mills et al. [100]	• Home energy scoring tool	• Energy use	Residential	US
	Daniel et al. [101]	• Accurate	• Heating load, cooling load	Residential	Australia
Statistical approach	Reilly et al. [102]	• Sensitivity analysis, Monte Carlo analysis	• Primary energy	Residential	Ireland
	Melo et al. [103]	• Artificial neural network (ANN)	• Energy consumption	Commercial	Brazil

Table 7
Literature review on the benchmarking a building's dynamic energy performance.

Approach		Authors	Methodology	Target	Building type	Location
Engineering approach	Equation	Burman et al. [107]	• Building physics method (NCM), Aggregated end-use (TM22)	• Energy use intensity (EUI)	School	UK
Statistical approach	Regression analysis	Chung et al. [108]	• Regression analysis	• Energy use intensity (EUI)	Commercial	Hong Kong
		Chung and Hui [109]	• Regression analysis	• Energy use intensity (EUI)	Office	Hong Kong
		Xuchao et al. [110]	• Regression analysis	• Energy use intensity (EUI), CO_2 emissions	Hotel	Singapore
	Neural network	Yalcintas [111]	• Artificial neural network (ANN)	• Energy use intensity (EUI)	Office	US
		Yalcintas et al. [122]	• Artificial neural network (ANN)	• Energy use intensity (EUI)	Office	US
		Hong et al. [113]	• Descriptive statistics, artificial neural network (ANN)	• Energy use intensity (EUI)	School	UK
		Hong et al. [114]	• Artificial neural network (ANN)	• Fossil fuel consumption, electricity consumption	School	UK
	Data envelope analysis	Lee [115]	• Data envelope analysis (DEA)	• Energy use intensity (EUI)	Office	Taiwan
		Lee and Lee [116]	• Data envelope analysis (DEA)	• Energy consumption	Office	Taiwan
		Lee [117]	• Data envelope analysis (DEA), cooling degree hour method	• Cooling energy consumption	Office	Taiwan
	Multiple attribute decision-making approach	Lee [118]	• Fuzzy measure, fuzzy integral	• Floor area, number of occupants, temperature, rain hours	Office	Taiwan
		Lee and Lin [106]	• Gray relational analysis	• Floor area, number of occupants, temperature, rain hours	Office	Taiwan
		Lee and Lin [119]	• Technique for Order Preference by Similarity to Ideal Solution	• Floor area, number of occupants, temperature, rain hours	Office	Taiwan
	Others	Farrou et al. [120]	• *k*-means algorithm	• Electrical consumption, thermal consumption	Hotel	Greece
Hybrid approach		Hernandez et al. [121]	• prEN15217:2005, EnergyPlus, Statistical mean	• Energy performance indicator (EPI)	School	Ireland
		Borgstein and Lamberts [122]	• Regression analysis, DesignBuilder	• Energy use intensity (EUI)	Bank	Brazil
		Shabunko et al. [123]	• Ordinary least square (OLS), Support vector machines (SVM), EnergyPlus	• Energy use intensity (EUI)	Residential	Brunei

- *Statistical approach:* It compares the measured energy consumption data with the statistical value from historical data to benchmark a building's dynamic energy performance. This can be done in numerous ways: (i) regression analysis; (ii) neural networks; (iii) data envelope analysis; and (iv) multiple-attribute decision-making approach. First, the simple way to establish benchmarking models for diagnosing a building's dynamic energy performance is by using regression analysis [108–110]. Xuchao et al. [110] used regression analysis to develop a benchmarking model for diagnosing the dynamic energy performance and greenhouse gas emissions of hotel buildings in Singapore. The results showed that the separate benchmarks for each star rating would allow more reasonable comparisons between hotels with more homogeneous physical and operational characteristics. Second, various studies established benchmarking models for diagnosing a building's dynamic energy performance using neural networks [111–114]. Hong et al. [113] used the descriptive statistics and the ANN model to develop a benchmarking model for diagnosing the dynamic energy performance of school buildings in the UK. The results showed that the ANN model could assess the operational energy efficiency of buildings more accurately than a simple method could, such as descriptive statistics. Third, other studies established benchmarking models for diagnosing a building's dynamic energy performance using data envelope analysis (DEA) [115–117]. Lee [115] used DEA to develop a benchmarking model for diagnosing the dynamic energy performance of office buildings in Taiwan. The results showed that it is possible to separately evaluate the impact of a building's energy performance management using DEA. Fourth, to evaluate a building's dynamic energy performance from the multi-objective perspective, some studies established benchmarking models for diagnosing a building's dynamic energy performance using multiple-attribute decision-making approaches [118,106,119]. Lee and Lin [106] used gray relational analysis, one of the multiple-attribute decision-making approaches, to develop a benchmarking model for diagnosing the dynamic energy performance of office buildings in Taiwan. The results showed that the proposed method could be reasonable and efficient for evaluating a building's dynamic energy performance.
- *Hybrid approach:* It uses both physical principles and historical data to benchmark a building's dynamic energy performance by comparing the measured energy consumption data with the developed benchmark. Borgstein and Lamberts [122] used both the engineering approach (i.e., simulation using the DesignBuilder software) and the statistical approach (i.e., regression analysis) to develop a benchmarking model for diagnosing the dynamic energy performance of bank buildings in Brazil. Although it is possible to develop a benchmarking model

using only a statistical approach, the results showed that the engineering approach could allow results validation, correction factor checking, and end-use energy consumption breakdown estimation.

4.2.2. Developing the operational rating model

Other previous studies developed an operational rating model for diagnosing a building's dynamic energy performance using various approaches, such as the calculation, simulation, and statistical approaches (refer to Table 8) [13,124–135].

- *Calculation approach:* Yan et al. [124], Yan et al. [125], and Florio and Teissier [126] used the calculation approach to develop a simplified operational rating model. The study aimed to use the proposed model when there was bound to be insufficient energy use data available. Yan et al. [125] developed a multi-level (i.e., building, system, and component levels) energy performance diagnosis method based on electricity and cooling energy balance. The study aimed to use the proposed model when there was bound to be insufficient energy use data available. The study also established a customized benchmarking method using the relative performance factor to diagnose the predicted energy performance level by comparing it with the expected energy performance level.
- *Simulation approach:* Eang and Priyadarsini [127], Tronchin and Fabbri [128], Menezes et al. [129], Yousif et al. [130], Xing et al. [131], and Wilde [132] used the simulation approach to investigate the performance gap between the asset ratings and the operational ratings. Tronchin and Fabbri [128] used three different simulation methods (i.e., operational rating based on energy bills, dynamic simulation with the DesignBuilder software, and simplified simulation with the BestClass software) to compare the results with the actual energy consumption of a residential building in Italy. The results showed that the DesignBuilder software is more acceptable than the BestClass software due to the simplified calculation method and input data of BestClass. Menezes et al. [129] developed five predictive models of electricity consumption using the TM22 methodology for diagnosing the dynamic energy performance of office buildings in the UK. The study used the monitoring data on electricity consumption and occupancy profiles to investigate the impact of using post-occupancy evaluation information. The results showed that it was possible to increase the accuracy of the model to within 3% of the actual electricity consumption by combining the monitoring data with predictive energy modeling. Yousif et al. [130] used two different simulation methods (i.e., the DesignBuilder software and the Energy Performance Rating of Dwellings Malta (EPRDM)) to compare the results with the actual energy consumption of a residential building in Malta. The results showed that the operational ratings were lower than the asset ratings of EPRDM and the DesignBuilder software, which means that the asset ratings overestimated the actual energy consumption of buildings.
- *Statistical approach:* Santamouris et al. [133], Ahmed et al. [134], Kabak et al. [135], and Koo et al. [13] used the statistical approach to develop fair and reliable criteria for establishing the operational ratings in a simple way. Santamouris et al. [133] used fuzzy clustering techniques to classify the dynamic energy performance of school buildings and to develop a new operational rating model in Greece. The results showed that the proposed model offered more robust classes while still avoiding non-balanced rating problems. Kabak et al. [135] applied a fuzzy analytic network process to the National Building Energy Performance Calculation Methodology in Turkey (BEP-TR) for categorizing the dynamic energy performance of residential buildings in a simpler way. The results showed that a fuzzy multi-criteria decision-making approach could determine the weights of the criteria in BEP-TR, which

Table 8
Literature review on the developing the operational rating model.

Approach	Authors	Methodology	Target	Building type	Location
Calculation approach	Yan et al. [124]	• Energy bill disaggregation	• Cooling load	Commercial	Hong Kong
	Yan et al. [125]	• Energy balance equations, Energy bill disaggregation	• Energy use intensity (EUI)	High-rise	Hong Kong
	Florio and Teissier [126]	• ENL to TABULA algorithm	• Energy label, Energy performance index (EPI)	Residential	France
Simulation approach	Eang and Priyadarsini [127]	• Energy Smart Labeling system	• Energy use intensity (EUI)	Office	Singapore
	Tronchin and Fabbri [128]	• Operational rating, DesignBuilder, BestClass	• Primary energy	Residential	Italy
	Menezes et al. [129]	• TM22, Monitoring	• Electricity consumption	Office	UK
	Yousif et al. [130]	• DesignBuilder, Energy Performance Rating of Dwellings Malta (EPRDM) software	• Electricity consumption	Residential	Malta
	Xing et al. [131]	• eQUEST	• Energy consumption, Energy performance rating	Office	China
	Wilde [132]	• Two-sample Kolmogorov–Smirnov (K–S) test, EnergyPlus	• Electricity consumption, gas consumption	School	UK
Statistical approach	Santamouris et al. [133]	• Intelligent fuzzy clustering techniques	• Energy consumption	School	Greece
	Ahmed et al. [134]	• Naïve Bayes, Decision tree, Support Vector Machine (SVM)	• Thermal comfort, Strongly day-lit rooms, Consequently schedule rooms for usage	Multi-function	Ireland
	Kabak et al. [135]	• Fuzzy Analytic Network Process, National Building Energy Performance Calculation Methodology in Turkey (BEP-TR)	• BEP-TR energy class	Residential	Turkey
	Koo et al. [13]	• Decision tree	• CO_2 emission density	Residential	Korea

makes it possible to categorize the dynamic energy performance of buildings in a simpler way. Koo et al. [13] used the decision tree to establish reasonable and fair criteria for the operational rating system of residential buildings in South Korea. The results showed that the irrationality of the conventional operational rating system (i.e., the overall-data-based rating system) has been resolved by considering the cluster formation based on the household size using the decision tree.

5. Retrofitting phase of a building's dynamic energy performance

Many previous studies analyzed several energy retrofit strategies for improving a building's dynamic energy performance, aiming to achieve net zero energy building (nZEB). Fig. 3 shows the graphical concept of the nZEB balance, plotting the weighted demand on the *x*-axis and the weighted supply on the *y*-axis [136]. The point of "reference building" represents the energy performance of a new building or an existing building before implementing the energy retrofit strategy. The pathway from the points of "reference building" to "net zero balance line" is given by means of two strategies: (i) reducing the energy demand (*x*-axis) by means of energy-saving techniques and (ii) increasing the energy supply (*y*-axis) by means of new and renewable energy systems to achieve the balance.

Meanwhile, a building's dynamic energy performance data should be collected from the simulation and experimental methods to enhance a building's dynamic energy performance. Generally, the experimental method can directly provide a building's dynamic energy performance, but it cannot be conducted under the same conditions of the external environment [137]. Thus, the simulation method is widely applied as an alternative method to obtain sufficient energy performance data. Meanwhile, it is necessary to pay more attention to the optimization, energy balance, and trade-off among different design elements. Thus, in most of the previous studies, the major consideration was given to various types of evaluation targets, algorithms and methods, and simulation and experimental tools.

5.1. Energy-saving techniques

A building's energy demand or consumption can be reduced by applying energy-saving techniques (i.e., the passive and active design techniques). All countries have established their respective building energy standards and design guidelines by considering the local climates as well as the prevailing architectural designs

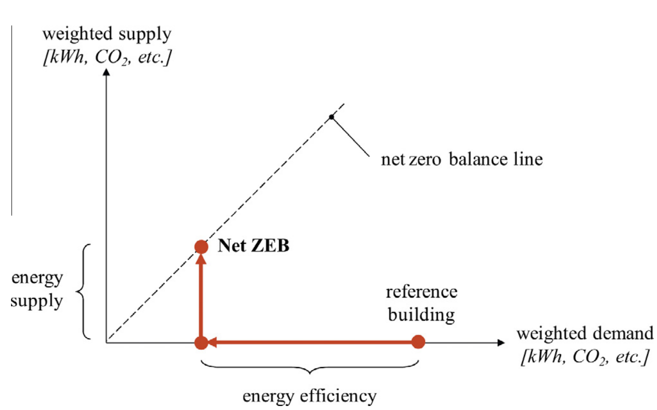

Fig. 3. Graphical concept of nZEB balance. *Source*: Sartori et al. [136] (License number: 3610780733711; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Energy and Buildings. This is a License Agreement provided by Copyright Clearance Center (CCC)).

and construction practices (e.g., the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Standard). Accordingly, the participants in construction projects need to design the building's dynamic energy performance in such a way as to meet the minimum criteria required by the local building energy standards. In this regard, the energy-saving techniques that have a significant effect on a building's dynamic energy performance can be largely divided into two categories: (i) the passive design techniques: thermal insulation, thermal mass, windows/glazing/daylighting/shading and reflective/green roof and (ii) the active design techniques: HVAC (heating, ventilation, and air conditioning), artificial lighting, and occupancy control).

Based on extensive literature review, this study summarized the previous studies as shown in Tables 9–11. The previous studies were arranged in a chronologically descending order in the presentation of the literature review on the energy-saving techniques for buildings. Table 9 shows a summary of the previous studies on the passive design techniques [138–148], and Table 10 shows a summary of the previous studies on the active design techniques [149–160]. Finally, Table 11 shows a summary of the previous studies on the combination of the passive and active design techniques [161–167].

5.1.1. Passive design techniques

Based on the literature review conducted in this study, it is necessary to consider the local prevailing climate conditions in different regions when establishing the optimal energy retrofit strategy using the passive design techniques, which can reduce a building's energy demand or consumption. The passive design techniques can be divided into four categories: (i) thermal insulation; (ii) thermal mass; (iii) windows/glazing/daylighting/shading; and (iv) reflective/green roof [138–148].

- *Thermal insulation:* The optimum thickness of insulation materials and the air gaps in building walls can have an effect on the building's dynamic energy performance. Generally, the thermal insulation is more effective in heating-dominated buildings in cold climates [139]. Pulselli et al. [146] evaluated the environmental effects of a plus-insulated wall for three regions (i.e., Berlin, Barcelona, and Palermo). The study highlighted the fact that the thermal-insulation performance of a building depends on the external climate conditions. The current research trend in the area of thermal insulation considers the cost energy effectiveness as well as the environmental-impact effectiveness.
- *Thermal mass:* Thermal mass is a property of a building's mass that enables it to store thermal energy, providing inertia against temperature fluctuations [140]. Scientifically, thermal mass is equivalent to heat capacity or thermal capacitance. Radhi [145] discussed the global warming and the energy consumption in the air-conditioned buildings in the hot climate of the United Arab Emirates. It was found that the energy used for cooling increased the global warming potential by 23.5% if the temperature in Al-Ain city would increase by 5.9 °C. The net CO_2 emissions could increase at about 5.4% over the next few decades. The simulation results showed that the passive design techniques such as thermal insulation and thermal mass would be more important to cope with global warming.
- *Windows/glazing/daylighting/shading:* It is necessary to consider the thermal, acoustic, visual, and solar performance of the window/glazing system in the conceptual design phase. The ratio of glazing in building façades has increased for the aesthetic purposes. Accordingly, the heating and cooling energy consumption has increased due to the direct solar radiation inside the building [144]. To address these issues, various energy-saving techniques, such as the use of tinted or colored glass, have been introduced to block the direct solar radiation. Tian et al. [141]

Table 9
Literature review on the passive design techniques.

Authors	Country	Building sector	Passive design techniques				Evaluation target			Algorithm/method	Simulation tool
			Thermal insulation	Thermal mass	Window/ glazing/daylight/ shading	Reflective/green roof	Energy/ thermal	Air quality/ Environmental impact	Cost		
Mahlia & Iqbal [138]	Maldives	Residential/ Commercial	○	–	–	–	○	–	○	Heat transfer Calculation	–
Gaterell and McEvoy [139]	UK	Residential	○	–	○	–	○	–	–	Simulation	TAS
Weir and Muneer [140]	UK	General, no specific building type	–	–	○	–	○	○	–	LCA	–
Tian et al. [141]	Hong Kong	Office	–	–	○	–	○	–	–	Window energy rating system (WERS)	DOE2/ADELINE
Boixo et al. [142]	Spain	Residential	–	–	–	○	○	–	○	Simulation	DOE
Kim et al. [143]	South Korea	Educational facility	–	–	–	○	○	○	○	Simulation	Energy plus
Hong et al. [144]	South Korea	Library			○	○	○	○	○	Simulation	Energy plus
Seo et al. [93]	South Korea	Residential	–	–	○	–	○	–	–	Lagrangian finite element model	Design builder/Visual basic application EXCEL
Radhi [145]	UAE	Residential	○	○	○	–	○	○	–	Simulation	Visual DOE
Pulselli et al. [146]	Berlin/ Barcelona/ Palermo	General, no specific building type	○	○	○	–	○	–	○	Energy analysis/ Energy evaluation	–
Ouedraogo et al. [147]	Burkina Faso	Office	○	–	○	–	○	–	–	Test reference year(TRY) selection algorithm	IES VE
Cheung et al. [148]	Hong Kong	High-rise Apartment	○	○	○	–	○	–	–	Simulation	TRNSYS

Table 10
Literature review on the active design techniques.

Authors	Country	Building sector	Active design techniques			Evaluation target			Control schemes	Algorithm/method	Simulation
			HVAC/ thermal	Artificial lighting	Occupancy control	Energy/ thermal	Air quality/ Environmental impact	Cost			
Aria and Akbari [149]	Canada	Office	○	○	–	○	–	○	Multi-hour optimization	Non-linear programming	MATLAB/DOE2
Marinakis et al. [150]	Greece	Office	○	○	○	○	–	○	ON/OFF scheduling/ programmed	Scheduling algorithm	Prototype Software Tool
Zavala [151]	USA	Commercial/ Office	○	–	○	○	○	○	Model predictive control (MPC)	AMPL modeling	Energy Plus and TRNSYS
Colmenar-Santos et al. [152]	Spain	Office	○	○	–	○	○	–	MPC control	Predictive control optimization tool	TRNSYS & INSEL
Liu et al. [153]	China	Office/ industry	○	○	–	○	–	○	–	Ordinal optimization(OO)/GA	Energy Plus
Wang and Tan [154]	Singapore	Office	–	○	○	○	–	–	Artificial neural network	Constrained non-linear programming	MATLAB Simulink
Goyal et al. [155]	USA	Commercial	○	–	○	○	○	–	MPC algorithm, feedback control, MPC control	Constrained time step optimization	MATLAB/IPOPT
Rezvan et al. [156]	Iran	Commercial	○	–	–	○	○	○	–	Standard simple and branch bound algorithm	Energy Plus
Ferreira et al. [157]	Portugal	Commercial	○	–	○	○	–	–	Discrete model-based predictive control	MOGA	Radial Basis function ANN
Pisello et al. [158]	USA	Commercial	○	○	○	○	–	–	Dynamic	Scheduling	Energy Plus
Eisenhower et al. [159]	USA	All	○	–	–	○	–	○	–	Support vector regression (meta-model) approach	Energy Plus
Ha et al. [160]	France	Residential/ Office	○	–	○	○	–	○	Dynamic predictive control scheduling mechanism	Mixed integer linear programming (MILP)	GNU Linear Programming Kit

Table 11
Literature review on the combination of the passive and active design techniques.

Authors	Country	Building sector	Energy saving techniques: Passive design: Thermal insulation	Thermal mass	Window/glazing/daylight/shading	Reflective/green roof	Active design: HVAC/thermal	Artificial lighting	Occupancy control	Evaluation target: Energy/thermal	Air quality/Environmental impact	Cost	Algorithm/method	Simulation
Wan et al. [161]	Hong Kong	Office	○	–	–	–	○	○	–	○	–	–	Simulation	Visual DOE 4.1
Guan [162]	Australia	Office	○	○	○	–	○	–	–	○	○	–	Pearson's correlation/dynamic interaction	DOE-2.1E
Lam et al. [163]	Hong Kong	Office	–	○	○	–	○	–	–	○	–	–	Simulation	DOE-2
Wan et al. [164]	China	Office	○	–	○	–	○	○	–	○	○	–	Principal component analysis (PCA)/Regression models	VisualDOE4.1
Hong et al. [165]	South Korea	Educational facility	○	–	○	–	–	○	–	○	○	○	Simulation	Energy Plus
Hong et al. [166]	South Korea	Educational facility	○	–	○	○	–	○	–	○	○	○	Simulation	Energy Plus
Koo et al. [167]	South Korea	Educational facility	–	–	○	–	○	○	–	○	○	○	Multi-objective optimization/GA/Simulation	Evolver/Energy Plus

developed energy rating systems for different glazing types, buildings, and climates. The proposed systems can be useful design tools for more environment-friendly and sustainable building development. The current research trend in windows/glazing/daylighting shows the development of simplified models by simultaneously considering the glazing type, blind type, and window-to-wall ratio [93].

- *Reflective/green roof:* The conventional roof reflects only the solar radiation within the range of 6% and 26%, and then it brings about excessive energy use in a building. To solve this problem, the reflective and green roof can be applied to a building. Boixo et al. [142] found that the reflective roof in the residential buildings in Spain could save 295 MW h in electricity consumption per year. Kim et al. [143] developed the optimal-scenario selection model by considering both the economic and environmental effect in implementing the green roof to educational facilities. In terms of only the economic value, the conventional roof system was superior to the green roof system, but by considering the environmental value, it was determined that the green roof (artificial soil + grass) is superior to the conventional roof system.

5.1.2. Active design techniques

Based on the literature review conducted in this study, the active design techniques can be divided into three categories: (i) the HAVC system; (ii) artificial lighting; and (iii) occupancy control. In particular, the current research trend in the active design techniques focused on the optimization of the active design control schemes [149–160]. By applying the optimization of the active design technique, about 30% energy savings can be achieved in office buildings [152]. That is, the potential reduction can be achieved by applying the automation system using a predictive control optimization tool. It was concluded that simulation models of HVAC systems and artificial lighting should be used for determining a proper system design in the design phase. Liu et al. [153] explored the building's energy efficient design for manufacturing plants. The study attempted to address an EnergyPlus-integrated overall energy consumption estimation framework. In addition, the ordinal optimization method was introduced to quantitatively guarantee a high probability of satisfactory designs while reducing the computation burden. Meanwhile, some previous studies considered occupancy control, such as the occupancy pattern, behavior, and learning preferences. Goyal et al. [155] proposed several control algorithms and compared their performance and complexity using the simulation method. In this study, the control algorithms used occupancy information to reduce energy consumption—over the conventional control algorithms—while maintaining the thermal comfort and indoor air quality. The simulation results showed that each of the proposed control algorithms led to a significant amount of energy savings, over the baseline conventional control algorithm, without sacrificing the occupants' health and comfort.

5.2. New and renewable energy systems

A building's energy supply can be achieved by applying new and renewable energy systems not only for large-scale energy production but also for stand-alone systems. The new and renewable energy systems can be largely divided into four categories: (i) PV system; (ii) solar thermal energy (STE) system; (iii) ground source heat pump (GSHP) system; and (iv) fuel cell system [168–208] (refer to Table 12).

5.2.1. PV system

Various factors should be considered to improve the performance of the PV system, which includes the regional factors (e.g.,

Table 12
Literature review on the new and renewable energy systems.

New renewable energy	Authors	Country	Building sector	System parameter	Evaluation target			Algorithm/method	Simulation
					Energy/thermal	Air quality/Environmental impact	Cost		
Photovoltaic system	Park et al. [168]	South Korea	Sunroom	Semi-transparent PV module/p-Si/In vertical window	○	–	–	Experimental	–
	Fossa et al. [169]	Italy	General, no specific building type	On vertical wall	○	–	–	Experimental	–
	Fung and Yang [170]	Hong Kong	General, no specific building type	Semi-transparent BIPV modules/In vertical window	○	–	–	Experimental	–
	Agrawal and Tiwari [171]	India	Laboratory	BIPV module/Facing south Tilt angle of 35°	○	–	–	Numerical study	–
	Chow et al. [172]	Macau	Hotel	Mono-crystal PV/Rooftop	○	–	–	Numerical simulation	ESP-r
	Yoon et al. [173]	South Korea	Research center	a-Si thin film/Facing 50° southwest/vertical window	○	–	–	Experimental/Numerical	ESP-r
	Guiavarch and Peuportier [174]	Paris	Residential	Multi-crystalline silicon PV/Window/Rooftop	○	–	–	Experimental/Numerical	COMFIE
	Hong et al. [18]	South Korea	Educational Facility	Rooftop	○	○	○	Optimization/GA/Simulation	RETScreen/ArcGiS
	Koo et al. [12]	South Korea	Educational Facility	Rooftop	○	○	○	Optimization/GA/Simulation	RETScreen/ArcGiS
Solar thermal energy system	Lamnatou et al. [175]	France	Educational Facility	Several configurations (in series/in parallel connection, etc.)	○	○	–	Experimental	–
	Liang et al. [176]	China	Test room	Air source heat pump(ASHP) + solar collector	○	–	–	Experimental	–
	Bakirci and Yuksel [177]	Turkey	Residential	12 solar collectors + thermal storage tank + water source heat pump	○	–	–	Experimental	–
	Li et al. [178]	China	Test room	DX-SAHP(solar collector/evaporator + heat pump)	○	–	–	Experimental	–
	Kalogirou [179]	Cyprus	Residential	Both systems: 5 m^2 collector area; the two systems have different materials	○	○	–	Numerical simulation	Polysun program
	Battisti and Corrado [180]	Italy	General, no specific building type	Integrated collector–storage, passive, water heating	○	○	–	LCA Simulation	SimaPro 5.0
	Otanicar and Golden [181]	USA	Phoenix metropolitan area/	Conventional vs. nanofluid collector, water heating	○	○	○	Numerical study	–
	Karagiorgas et al. [182]	Greece	Office	Solar collector + ASHP	○	–	–	Experimental/simulation	TRNSYS/TSAGAIR
Ground source heat pump system	Benli [183]	Turkey	Test room	Horizontal closed-loop GHE and phase change materials (PCM)	○	–	–	Experimental	–
	Morrone et al. [184]	Italy	General, no specific building type	–	○	–	○	Numerical simulation	PILESIM2/TRNSYS
	Nam and Chae [185]	South Korea	Residential	Horizontal system	○	–	–	Numerical simulation/Finite element method	FEFLOW
	Chargui et al. [186]	Tunisia	Residential	Geothermal heat pump in heating mode	○	–	–	Numerical simulation	TRNSYS
	Alavy et al. [187]	Canada	10 buildings in Toronto	Optimum hybrid GSHP	○	–	○	Numerical simulation	eQUEST/GLD

Table 12 (*continued*)

New renewable energy	Authors	Country	Building sector	System parameter	Evaluation target			Algorithm/method	Simulation
					Energy/ thermal	Air quality/ Environmental impact	Cost		
	Fan et al. [188]	China	Office	Vertical dual-function geothermal heat exchanger in an integrated soil cold storage and GSHP	○	–	–	Experimental/Numerical study	–
	Gan et al. [189]	UK	Test room	Rain-water and ground as heat sources/sinks	○	–	–	Experiment/ simulation/computational fluid dynamics	FLUENT
Fuel cell system	Mahlia and Chan [190]	Malaysia	Residential	PEMFC	○	–	○	Numerical simulation	HOMER
	Guizzi and Manno [191]	Italy	Data center	PEMFC	○	–	○	Numerical study	–
	Oh et al. [192]	South Korea	Residential	PEMFC	○	–	○	Thermoeconomic analysis	–
	Chen and Ni [193]	Hong Kong	Hotel	SOFC	○	–	○	Numerical study	–
	Wakui and Yokoyama [194]	Japan	Residential	SOFC	○	○	–	Numerical study	–
	Aki et al. [195]	Japan	Residential	PEMFC	○	○	–	Experimental	–
	Fong and Lee [196]	Hong Kong	Residential	SOFC	○	○	–	Numerical study	–
	Kim et al. [197]	South Korea	Residential/ Educational facility	PEMFC/MCFC	○	○	○	Numerical simulation	RETScreen
	Hong et al. [198]	South Korea	Residential	PEMFC/MCFC	○	○	○	Numerical simulation	RETScreen

latitude, monthly average daily solar radiation, etc.) and the onsite installation factor (e.g., azimuth, slope, panel type, etc.). Especially, in the design phase, the onsite installation factor should be carefully considered to obtain the optimal solution of the PV system. Many previous studies used experimental and numerical simulations for evaluating the performance of the PV system [12,18,168–174].

Park et al. [168] evaluated the effects of the thermal characteristics of the semi-transparent PV module on its electricity generation performance. The results showed that the electricity generation performance decreased by 0.48% (under the standard test condition) and 0.52% (under the outdoor conditions) when the PV module's temperature increased by 1 °C. Chow et al. [172] used the ESP-r simulation tool to analyze how the weather conditions and building's operating strategy had a significant effect on the productivity of the PV system. The results showed that the effective cooling of a PV module could increase its electricity generation performance. Yoon et al. [173] used both the experimental and numerical simulation method to analyze the windows transparent thin-film amorphous-silicon solar cells. The results showed that up to 47% energy savings can be achieved by considering the orientation and its shading effect. Hong et al. [18] developed a GIS-based optimization model for the rooftop PV system by considering the regional factors and onsite installation factors. The results showed that the regional factor, the panel's azimuth, and the panel's slope registered a 1.12-, 1.62-, and 1.37-fold difference in electricity generation, respectively.

5.2.2. STE system

There are very similar characteristics between the STE system and the PV system, but the STE system used the solar thermal collectors instead of the PV modules. Various factors should be considered to improve the performance of the STE system, including the regional factors and the onsite installation factors. As the STE system should be linked with the building's heat pump system, it is necessary to carefully investigate the building's heat pump system in advance. Many previous studies used the experimental and numerical simulations for evaluating the performance of the STE system [175–182].

Lamnatou et al. [175] considered the embodied energy and carbon emissions and multiple scenarios to conduct a life cycle analysis of a building-integrated solar thermal collector at the University of Corsica in France. The results showed that the environmental performance of the STE system could be considerably improved by installing parallel solar thermal collectors. Kalogirou [179] used the Polysun simulation tool to analyze the life cycle assessment and life cycle cost of the STE system. The results showed that up to around 40% energy savings could be achieved when applying the STE system to the space heating and hot-water system. Karagiorgas et al. [182] used both the experimental and numerical simulation methods to find the optimal seasonal operation scheme of the heating system in a bioclimatic building. The results showed that only warm air from the solar collector or mixed with outdoor air could be supplied into the evaporator of the heat pump in winter. Also, direct-space-heating air could be supplied by solar collectors in spring and fall.

5.2.3. GSHP system

The GSHP system can be used for space heating and cooling in buildings [183–186]. The GSHP system transfers ground heat into buildings in winter, and emits the heat out of buildings in summer [187–189]. The GSHP system consists of a heat pump, a ground heat exchanger (GHE) to collect the heat from the ground, and a pump to circulate a thermal fluid between the heat pump and the GHE. Many previous studies used experimental and numerical simulations for evaluating the performance of the GSHP system.

Gan et al. [183] conducted experimental and numerical simulations to evaluate the performance of the heat pump system designed to use rainwater and ground source: (i) a refrigerant in a closed-loop GHE transferred the heat between the heat pump and rainwater into a storage tank; and (ii) the other GHE transferred the heat between the stored rainwater and the surrounding soil into a storage tank. The results showed that the heating or cooling capacity of the GSHP system would increase if the water temperatures would be controlled and kept within a certain range. Morrone et al. [185] used the PILESIM2 software to conduct a technical and economic feasibility study on the GSHP system for residential buildings. The results showed that the economic benefit in the cold climate was larger than that in the mild climate.

5.2.4. Fuel cell system

A fuel-cell-based combined heat and power (FCCHP) system is currently being promoted as one of the core green technologies, with the following advantages [190–193]: (i) all-weather power generation system; (ii) high-efficiency fuel cells; and (iii) minimum installation area per unit power generation. Many previous studies used experimental and numerical simulations for evaluating the performance of the FCCHP system [194–198].

Mahlia et al. [190] assessed the economic effect of a 1 kW polymer electrolyte membrane fuel cell (PEMFC) system on a household in Malaysia. The results showed that there was no cost-effective scenario even though the PEMFC could reduce the primary energy usage by up to 30–40%. Oh et al. [192] evaluated the economic value of a 1 kW PEMFC for a household in South Korea. The unit cost of electricity was estimated by considering the results of thermo-economic analysis and the economic benefit. The results showed that approximately 25% energy cost savings could be achieved by implementing the PEMFC in the spring and fall seasons. Fong et al. [196] considered two operating schemes of a solid oxide fuel cell (SOFC) system in a high-rise building. This study evaluated the environmental performance in terms of CO_2 mitigation and electricity savings. When the electricity demand of a given building was fully met by SOFC, the CO_2 mitigation and electricity savings could be achieved at 51.4% and 7.1%, respectively.

5.3. Hybrid system

The recent studies highlighted the emerging role of the application of the hybrid system in developing green buildings [199–208] (refer to Table 13). Alvarez et al. [199] implemented the practical nonlinear model predictive control (PNMPC) controller to control the building's thermal comfort. The study conducted a case study that included the HVAC system with the PV and STE systems. The results showed that the PNMPC controller could maintain the thermal comfort in all the rooms, resulting in a comfort thermal index close to zero. Deng et al. [203] proposed the energy supply concepts in Shanghai (humid) and Madrid (dry). A case study that included the thermal mass, shading, and HVAC system with the PV and STE systems was conducted. The results showed that the PV system's performance and indoor comfort were satisfied under Shanghai's and Madrid's weathers. As a result, the energy supply concepts need to be more customized for different weathers (i.e., the dehumidification device for Shanghai's climate and the humidification device for Madrid's climate).

Table 13
Literature review on the combination of the energy saving techniques and new and renewable energy systems.

Authors	Country	Building sector	Energy saving techniques		New renewable energy	Evaluation target			Algorithm/ method	Simulation
			Passive design	Active design		Energy/ thermal	Air quality/ Environmental impact	Cost		
Álvarez et al. [199]	Spain	Office	–	HVAC/ Occupancy control	PV/STE	○	–	○	Lagrangian dual method	ANN MATLAB
Yang and Wang [200]	USA	All	–	HVAC/ Lighting/ Occupancy control	PV	○	○	–	Fuzzy controller with particle swarrn optimization	MATLAB/GUI
Dagdougui et al. [201]	Italy	Residential	–	HVAC	PV/STE/ BM/WT	○	–	–	Integer programming, stochastic programming, global optimization/ Experimental	LINDO Systems Optimization software
Zhu et al. [202]	USA	Residential	Thermal insulation/ Thermal mass/ Window	HVAC	PV/STE	○	–	○	Numerical simulation/ Experimental	Energy10 and eQUEST3.6
Deng et al. [203]	China/ Spain	Residential	Thermal mass/ shading	HVAC	PV/STE	○	○	–	Simulation/ Experimental	TRNSYS/ INSEL
Fong and Lee [204]	Hong Kong	Residential	–	–	PV/STE/ WT	○	–	–	Numerical simulation	TRNSYS/TESS
Hong et al. [205]	South Korea	Educational facility	–	–	PV/STE/ GSHP/WT	○	○	○	Numerical simulation/ Sensitivity analysis	RETScreen/ ECOTECH
Hong et al. [206]	South Korea	Residential	Window	HVAC/ Lighting	PV	○	○	○	Simulation	EnergyPlus
Ren et al. [207]	Australia	Residential	–	–	PV/STE	○	○	○	Atmosphere–ocean general circulation models (AOGCMs)	AccuRate
Stojanović and Akander [208]	Sweden	Residential	–	–	STE/GSHP	○	–	–	Experimental	–

6. Application of a building's dynamic energy performance management by phase

This study provides the application of a building's dynamic energy performance management by phase (i.e., the monitoring, diagnosing, and retrofitting phases) so that potential readers could understand the application in the previous studies more clearly.

6.1. Monitoring phase

As mentioned in Section 3, the GIS, LiDAR data, and IRT method for monitoring a building's dynamic energy performance should be used in the urban-based built environments.

First, from the macro point of view, the previous studies used the GIS and LiDAR data. For example, Kim et al. [209] developed the energy monitoring system (EnerGIS) as part of the energy-integrated urban planning and management support system. The study aimed to monitor and visualize the energy usage from city to building scale. EnerGIS has two characteristics: (i) a monitoring database in a 3D urban environment and (ii) a visualization strategy using Google Earth plug-in.

- *Monitoring database in the 3D urban environment:* The monitoring database consists of three types of data: city information data, energy usage data, and environmental GIS data. Especially, energy usage data (e.g., CO_2 density, temperature, and humidity) were collected from the wireless environment sensors installed in the target building in real time.
- *Visualization strategy using Google Earth plug-in:* The massive monitoring database for the 3D urban environment was visualized and monitored using Google Earth plug-in. Also, four levels of details (e.g., mesh grid, block, building, and floor) were adopted to reduce the complexity in visualizing the 3D urban environment.

Meanwhile, EnerGIS can be utilized for the following purposes. First, as shown in Fig. 4, according to the purpose of the analysis, EnerGIS can analyze the energy usage by level. For example, if the user wants to analyze the city-based energy usage, it can be analyzed in the mesh grid level, and if the user wants to analyze the building-based energy usage, it can be analyzed in the building or floor level. Second, EnerGIS can provide information about buildings with the best and worst energy performance. For example, compared to the surrounding buildings, buildings with higher energy consumption are marked in green whereas buildings with lower electricity consumption are marked in red (refer to Fig. 5). Ultimately, using the proposed EnerGIS, it aimed to promote all the citizens to participate in building energy saving.

Second, from the micro point of view, the previous studies used the IRT method. Mukhopadhyaya et al. [210] conducted thermal-performance monitoring for the building insulation panel (VIP) retrofitted wall system in Canada's construction industry (refer to Fig. 6). The results of this study can be summarized in two aspects: (i) a monitoring database for three years and (ii) an indicator for evaluating the thermal performance.

- *Monitoring database for three years:* This study conducted thermal-performance monitoring for VIP for three years (i.e., 1st period: from December 13, 2011 to April 15, 2012; 2nd period: from December 5, 2012 to May 23, 2013; and 3rd period: from November 1, 2013 to January 9, 2014).

Fig. 4. Choropleth map with different levels of detail: block, building, and floor. *Source*: Kim et al. [209] (License number: 3610781193903; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Automation in Construction. This is a License Agreement provided by Copyright Clearance Center (CCC)).

Fig. 5. Leader as tabular and leaderboard views within Google Earth plug-in. *Source*: Kim et al. [209] (License number: 3610781193903; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Automation in Construction. This is a License Agreement provided by Copyright Clearance Center (CCC)).

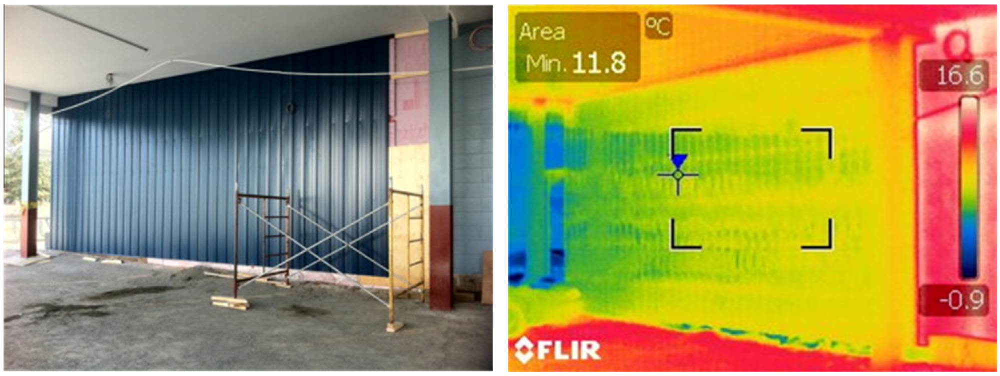

Fig. 6. Insulation (left) and infrared images of the wall with vacuum insulation panels. *Source*: Mukhopadhyaya et al. [210] (License number: 3610781418900; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Energy and Buildings. This is a License Agreement provided by Copyright Clearance Center (CCC)).

- *Indicator for evaluating the thermal performance:* This study used the percentage temperature difference across the insulation layers to conduct thermal-performance monitoring for VIP. The larger the percentage temperature difference is, the greater the effectiveness of VIP.

The thermal-performance monitoring of VIP can be summarized as follows. First, if the VIP-foam sandwich (i.e., the first layer adjacent to the existing block wall – VIP insulation – the second layer adjacent to the sell sliding) is to be installed in the subarctic Canadian climate, the effectiveness of the energy retrofit can be achieved. Second, through thermal-performance monitoring for three years (2011–2014), it was found that significant aging or damage has not occurred in the VIP insulation in the extreme cold climate.

6.2. Diagnosing phase

As mentioned in Section 4, one of the main concerns in diagnosing a building's dynamic energy performance is to overcome the performance gap between the asset ratings and the operational ratings. As a part of this concern, Wilde [132] investigated the performance gap in the UK and identified three main types of performance gap: (i) mismatch between the first-principle predictions and measurements; (ii) mismatch between the machine learning predictions and measurements; and (iii) mismatch between the energy performance ratings from predicted energy data (i.e., EPC) and measured energy data (i.e., DEC) (refer to Fig. 7).

Among these types of performance gap, the regulation side appears to have different energy labels from A to G for EPC and DEC in the UK, indicating a distinctive performance gap between the predicted and measured energy data. As shown in Fig. 8, the comparison between EPC and DEC for the same building revealed that only two out of 20 cases had the same labeling while the other cases resulted in a better EPC rating than DEC rating.

In the UK, EPC is related to the asset rating, which evaluates the energy performance based on the physical characteristics of a building, while DEC is related to the operational rating, which evaluates the energy performance based on the actual energy use of a building. Two types of energy certificates are implemented in

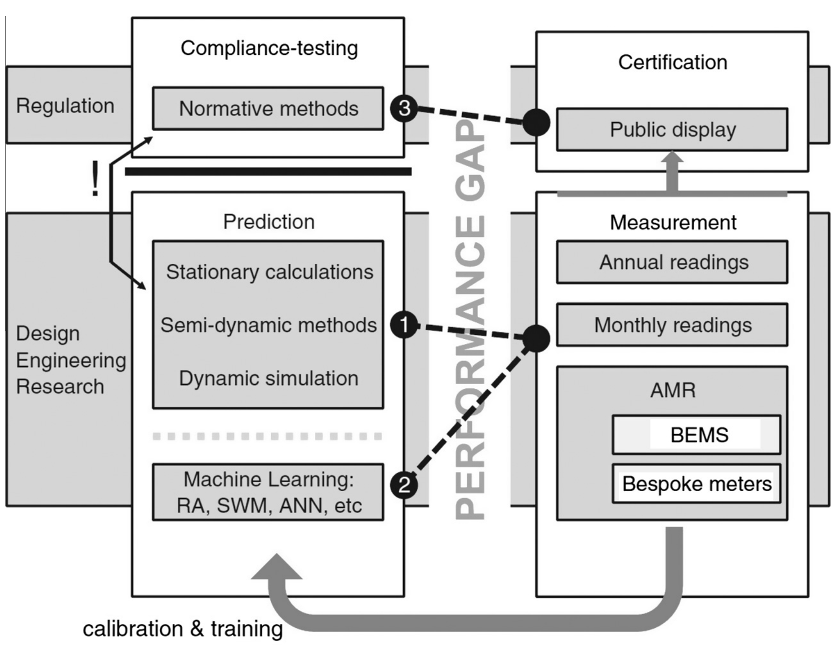

Fig. 7. Conceptual map of various views of the performance gap. *Source*: Wilde [132] (License number: 3610790147659; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Automation in Construction. This is a License Agreement provided by Copyright Clearance Center (CCC)).

	Credentials	Building type	EPC	DEC
building 1	BREEAM Excellent	court	B	D
building 2	BREEAM Excellent	court	B	E
building 3	BREEAM Excellent	data centre	A	F
building 4	BREEAM Excellent	education	B	F
building 5	BREEAM Excellent	education	B	D
building 6	BREEAM Excellent	education	B	D
building 7	BREEAM Excellent	office	B	C
building 8	BREEAM Excellent	office	A+	E
building 9	BREEAM Outstanding	education	B	G
building 10	BREEAM Excellent	court	D	D
building 11	BREEAM Excellent	education	C	C
building 12	BREEAM Excellent	education	B	C
building 13	BREEAM Excellent	education	B	E
building 14	passivehouse	education	A+	B
building 15	concrete center case	education	B	E
building 16	concrete center case	education	B	F
building 17	RIBA prize	office	A	B
building 18	RIBA prize	office	B	C
building 19	RIBA prize	healthcare	B	E
building 20	RIBA prize	education	B	D

Fig. 8. Comparison of outcomes of legislative energy assessment in the UK. *Source*: Wilde [132] (License number: 3610790147659; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Automation in Construction. This is a License Agreement provided by Copyright Clearance Center (CCC)).

different situations: (i) EPC is used for all buildings when they are constructed, sold, or rented; and (ii) DEC is used for large, public buildings and should be displayed for those buildings [211]. Fig. 9 shows an example of EPC and DEC for non-domestic buildings in the UK.

To reduce this performance gap, Menezes et al. [129] conducted a case study both for evaluating the energy performance of an office building in London using the TM22 methodology (one of the most widely recognized tools based on the measured energy use in the UK) and for monitoring the electricity consumption and occupancy patterns for more accurate predictions. To conduct a case study, this study developed five predictive models of electricity consumption: (i) using the TM22 methodology for models 1 and 2; and (ii) using measured data for models 3–5. Detailed descriptions of these five models are provided below [129].

- *Model (i)*: The typical compliance model using the lighting specifications from the design brief, using the simplified building energy model (SBEM) standard occupancy hours and overlooking small power and catering equipment.
- *Model (ii)*: An enhanced compliance model using the industry rules of thumb to account for small power loads, but overlooking catering equipment.
- *Model (iii)*: An initial bespoke model using the monitored data for the installed lighting load as well as the measured electricity demand for basic small power and catering equipment. The SBEM standard occupancy hours were used to account for an 80% usage factor of small power equipment.
- *Model (iv)*: An intermediate bespoke model using the monitored data for the installed lighting as well as the measured electricity demand for all small power and catering equipment. The SBEM standard occupancy hours were used to account for all the usage factors of small power equipment.
- *Model (v)*: An advanced bespoke model using the monitored data for the installed lighting as well as the measured electricity demand for all small power and catering equipment. The actual monitored occupancy hours were applied to all the lighting, small power, and catering equipment.

As shown in Fig. 10, the prediction results from the aforementioned five models were compared with the actual electricity consumption and two benchmark values based on Energy Consumption Guide 19 (ECON 19) (benchmarks for the typical and best-practice energy consumption for lighting, small power, and catering in standard air-conditioned office buildings with floor areas between 2000 m^2 and 8000 m^2). It was found that the increased details of the prediction models resulted in incremental increases in the predicted annual electricity consumption. Especially, in model 5, the predicted electricity consumption came within 3% of the error rate from the actual electricity consumption of the building, which indicates that the monitored occupancy hours can improve the prediction accuracy of the developed model.

6.3. Retrofitting phase

As mentioned in Section 5, energy-saving techniques and the new and renewable energy system should be used to establish an energy retrofit strategy for improving a building's dynamic energy performance. Kurnitzki et al. [212] established the system boundaries of the delivered energy in a building. First, the passive design has an effect on the “ENERGY NEED” box, which represents a building's energy needs for heating, cooling, ventilation, domestic hot water, lighting, and appliances. Second, the active design and the new and renewable energy system have an effect on the “BUILDING TECHNICAL SYSTEMS” box, which represents the energy supply system in a building. The energy used in a building

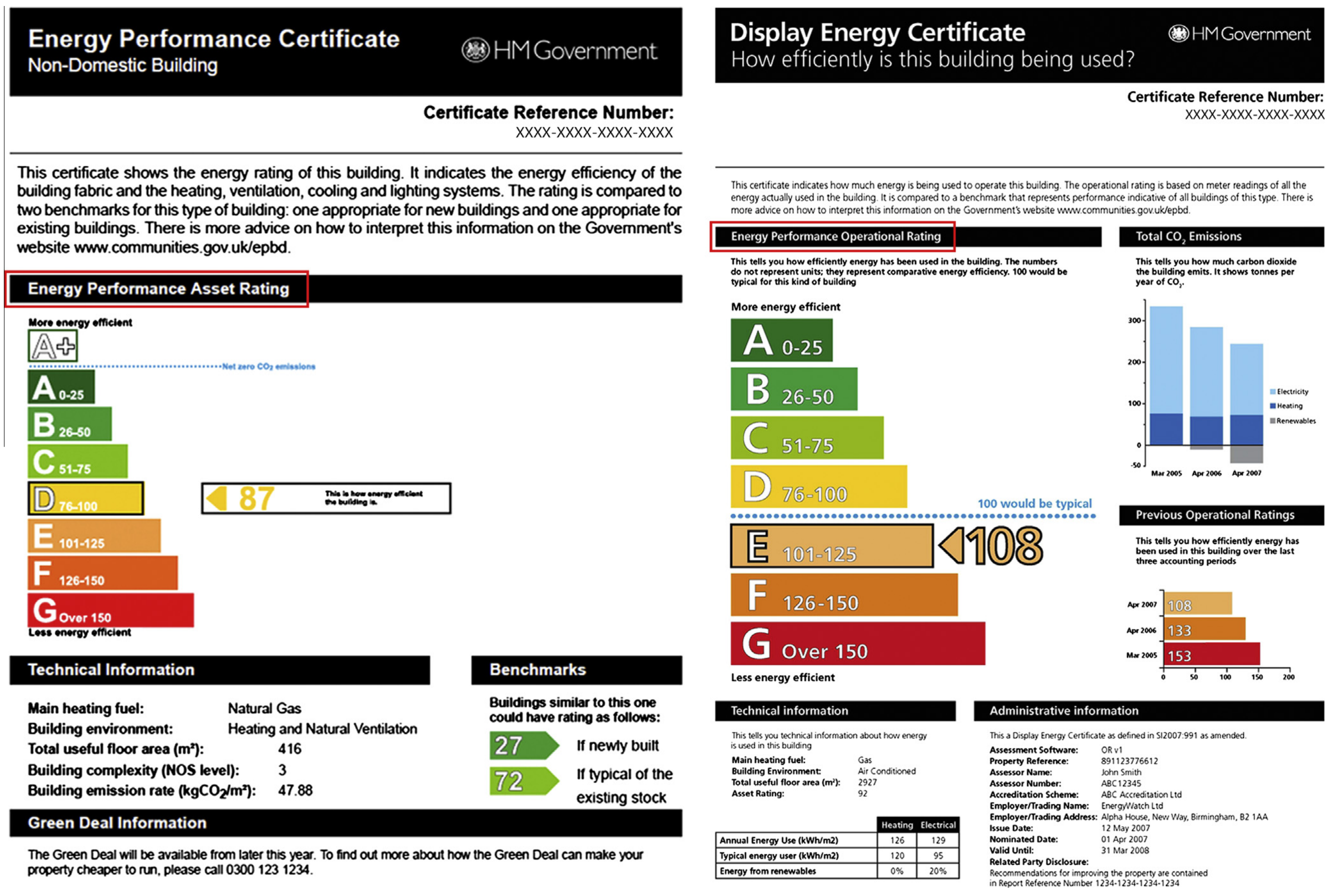

Fig. 9. An example of EPC (left) and DEC (right) for non-domestic buildings in the UK.

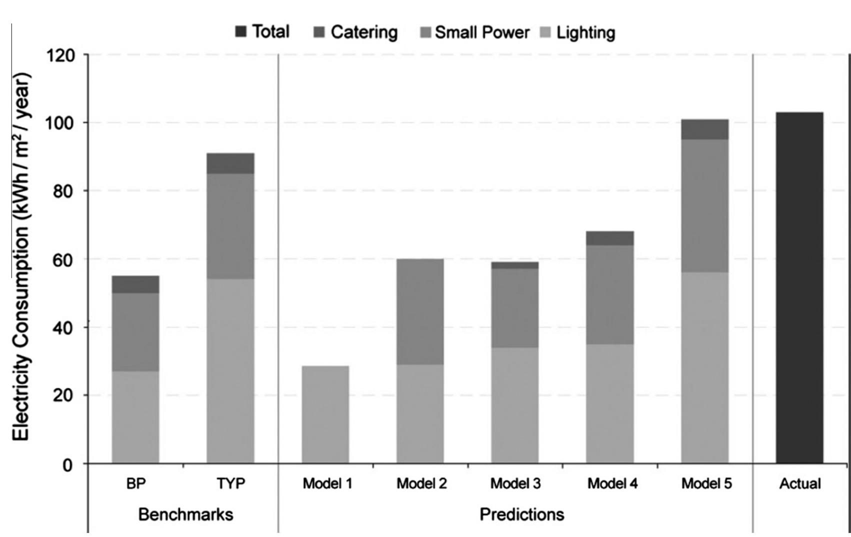

Fig. 10. Comparison of benchmarks, predicted and actual electricity consumption. *Source*: Menezes et al. [129] (License number: 3610790451196; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Applied Energy. This is a License Agreement provided by Copyright Clearance Center (CCC)).

can be achieved from the delivered energy or from the onsite renewable energy.

Meanwhile, the energy retrofit strategy should be established by simultaneously considering several techniques, such as the passive design, the active design, and the new and renewable energy system. The previous studies used the simulation and experimental methods for enhancing a building's dynamic energy.

First, some previous studies used the simulation method in the following process: (i) analysis of historical climate data; (ii) preparation of future weather data; (iii) analysis of simulation results; and (iv) sensitivity study and adaptation strategies. Guan [162] discussed the effects of climate change on the air-conditioned buildings in Australia. Case studies were conducted in a major Australian city considering several energy-saving techniques (e.g., insulation, window-to-wall ratio, and window glass type). It was found that depending on the assumed future climate scenarios, the total energy use of the Australian office buildings may decrease within the range from 1.24% to 3.20%.

Second, some previous studies used the experimental method from the short- and long-term perspectives. Stojanović and Akander [208] analyzed the long-term performance test of a full-scale solar-assisted heat pump system (SAHPS) that consists of the roof-integrated unglazed STE and the ground heat source for residential heating in Nordic climate conditions (refer to Fig. 11). The analysis focused on the system performance (i.e., the seasonal performance factor (SPF)). It was found that the system performance was $SPF_{HeatPump} = 2.85$ and $SPF_{SAHPS} = 2.09$.

Third, some previous studies used the simulation and experimental methods in the following process: (i) establishment of the baseline building (i.e., one using the conventional methods) and the modified building (i.e., one with the energy-saving techniques and the new and renewable energy system); (ii) comparison of the measured data with the building simulation and experiment results; and (iii) sensitivity study and evaluation of various adaptation strategies. The following studies analyzed the whole building system by simultaneously considering the variables from several areas. Dagdougui et al. [201] presented a hybrid model to integrate the various new and renewable energy systems into a storage device, and optimized a hybrid model for the energy supply of a green building (as shown in Fig. 12). Zhu et al. [202] analyzed the comprehensive energy and economic aspects of a zero-energy house and a conventional house located in Las Vegas, USA. This study considered energy-saving techniques and the new and renewable energy system to establish a zero-energy house that is a modified version of the baseline house (i.e., a conventional house). According to the measured and simulated data, the energy performance of the zero-energy house is superior to that of the baseline house.

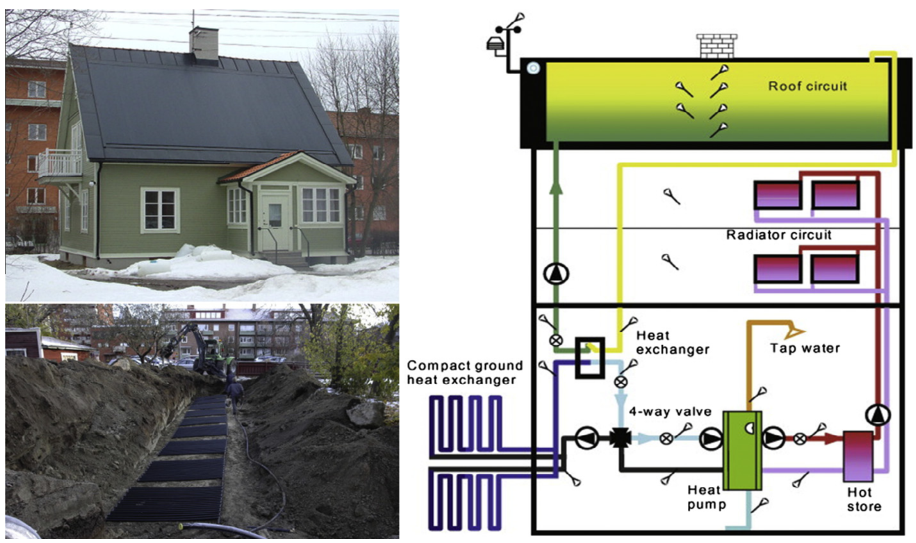

Fig. 11. Full-scale solar-assisted heat pump system. *Source*: Stojanović and Akander [208] (License number: 3610791153755; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Applied Thermal Engineering. This is a License Agreement provided by Copyright Clearance Center (CCC)).

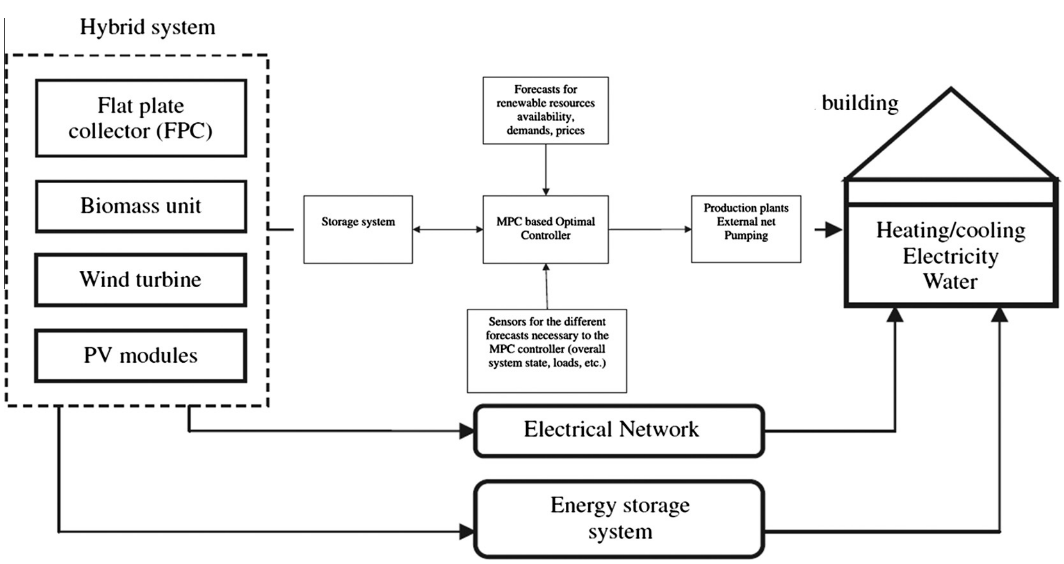

Fig. 12. The building MPC-based architecture and energy flow. *Source*: Dagdougui et al. [201] (License number: 3610791286969; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Energy Conversion and Management. This is a License Agreement provided by Copyright Clearance Center (CCC)).

7. Challenges and opportunities with regard to sustainable construction management strategies

As mentioned in Sections 3–6, there have been several studies in terms of the major phases of a building's dynamic energy performance management. First, in the monitoring phase, using GIS and LiDAR from the macro point of view or the IRT method from the micro point of view, previous studies have been actively carried out to visualize a monitoring strategy related to a building's dynamic energy performance from the urban-based ***per spective [21–67]. Second, in the diagnosing phase, using the estimation method (i.e., asset rating) in the design phase and the measurement method (i.e., operational rating) in the operation and maintenance phase, previous studies have been actively carried out to develop a diagnosing strategy related to a building's dynamic energy performance [68–135]. Third, in the retrofitting phase, using the energy-saving techniques and the new and renewable energy systems, previous studies have been actively carried out to develop a retrofitting strategy related to a building's dynamic energy performance [136–208].

Based on the extensive literature review above, it was concluded that there are several challenges and opportunities in sustainable construction management strategies for monitoring, diagnosing, and retrofitting the building's dynamic energy performance in the operation and maintenance phase. Therefore, this study suggests the future directions from the following eight viewpoints so as to overcome the possible challenges and to investigate the potential opportunities in a large complex system in terms of an "*Urban Organism*".

7.1. Integrating the monitoring phase into the diagnosing and retrofitting phases

This study subdivides the major phases of a building's dynamic energy performance management into three phases: the monitoring, diagnosing, and retrofitting phases. For these major phases to be effective, the following issues should be considered. First, in the monitoring phase, the building's dynamic energy performance should be systematically and continuously monitored. Second, it is necessary to dynamically link the measured data in the monitoring phase to the following phases (i.e., the diagnosing and retrofitting phases). Third, a cyclic feedback system should be established to link the improved energy performance (once the energy retrofit strategy is applied to the existing buildings in the retrofitting phase) to the monitoring phase.

Previous studies on the monitoring of a building's dynamic energy performance have considered the monitoring indexes in three aspects: (i) the research for visualizing a building's energy consumption (e.g., the electricity or gas energy consumption in residential buildings or educational facilities) [33–40]; (ii) the research for visualizing the potential of new and renewable energy resources (e.g., solar energy, geothermal energy, wind energy, etc.) [12,18,41–51]; and (iii) the research for visualizing the performance of the building envelop (e.g., windows, doors, wall, etc.) [57–67]. The aforementioned previous studies aimed to visualize the current status of the monitoring indexes, however, they did not link the analysis results in the monitoring phase into the building's energy performance certificate in the diagnosing phase (e.g., the display energy certificate for the public buildings in the UK). In addition, the monitoring indexes should be utilized for determining the optimal energy retrofit strategy in the retrofitting phase (e.g., the monthly average daily solar radiation for estimating the electricity generation of the photovoltaic system).

7.2. Visualizing a building's dynamic energy performance using real-time data

Monitoring indexes should be available not only for establishing the diagnosing and retrofitting strategies but also for promoting positive behavior in the building occupants (e.g., the voluntary participation of all the residents in the energy-saving campaign). Toward this end, the following factors should be considered. First, using the sensing and actuation technology, it is necessary to accumulate real-time data on a building's dynamic energy performance and the associated surrounding environment (e.g., room temperature, room humidity, number of persons in the room, etc.). Second, based on the real-time data, visualization should be conducted for the decision-making on the building's dynamic energy performance so that human perception and response can be immediately carried out.

Previous studies on the monitoring of a building's dynamic energy performance considered the yearly- or monthly-based data rather than the real-time data: (i) the previous studies using the yearly-based data (e.g., energy performance certificate, reserves and production of the world's energy resources, global climate change, etc.) [213–216] and (ii) the previous studies using the monthly-based data (e.g., monthly average daily solar radiation for estimating the electricity generation of the photovoltaic system, monthly electricity and gas energy consumption for establishing the optimal implementation strategy of a fuel-cell system, etc.) [15,41–43,197,198]. The aforementioned previous studies aimed to establish the energy policy from the national or local perspective and to establish the optimal energy retrofit strategy from the viewpoint of a single building. These efforts, however, are not enough to cope with the global climate change. Therefore, using real-time data, it is necessary to create a positive environment where human perception and response can be immediately carried out. For example, Fig. 13 shows the visualized carbon footprint map in Seoul, South Korea.

7.3. Retrieving valuable information from the big data in a large city

To monitor a building's dynamic energy performance from the viewpoint of "*Urban Organism*", it is necessary to provide the monitoring indexes from the national or local perspective as well as those from the viewpoint of a single building. Toward this end, the following factors should be considered. First, the data mining or machine learning technique should be implemented to retrieve valuable information from the big data in a large city [13–17,41–43,213–221]. This is because it is very difficult to provide the monitoring indexes from the national or local perspective. That is, it is extremely difficult to collect and establish a database on the physical characteristics and energy performance data of numerous buildings in a city, and to provide the necessary information to a suitable place in a timely manner. Second, the data retrieved from the monitoring phase should be converted into valuable information that can be used in the following diagnosing and retrofitting phases. For example, Fig. 14 shows the current status of a building's dynamic energy performance, its comparison values, and its energy retrofit strategy. That is to say, it should be possible to provide information on the current status of the building's energy performance, information on the energy performances of similar buildings as comparison values, and information for determining the optimal energy retrofit strategy.

7.4. Developing a carbon-integrated management system as a large complex system

This study suggests the future direction of system integration for the development of a carbon-integrated management system

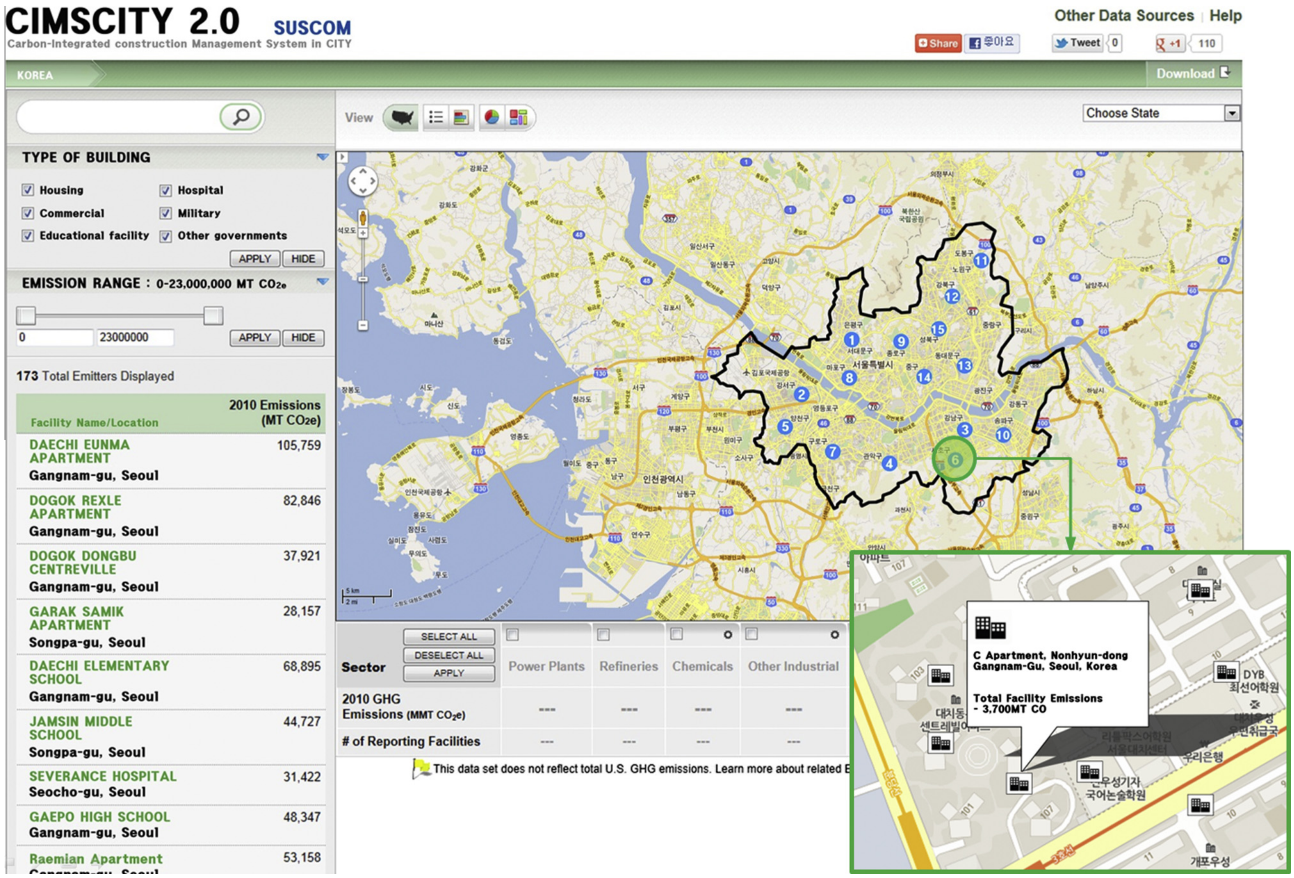

Fig. 13. Visualized carbon footprint map in Seoul, South Korea.

as a large complex system in terms of an "*Urban Organism*". That is, this study provides the holistic approach for developing the *Carbon Integrated Management System for monitoring, diagnosing and retrofitting the building's dynamic energy performance in a City, an urban organism (CIMSCity)* so as to minimize the carbon emissions in the operation and maintenance phase of the building sector and to achieve the energy-efficient and low-emission buildings [11].

Fig. 15 shows the framework for the development of CIMSCity, which can be used for integrating the various functions by phase (i.e., the monitoring, diagnosing, and retrofitting phases) in the context of the sustainable construction management strategies for systematically controlling a building's dynamic energy performance. The framework consists of four parts.

- *Part I:* Carbon emission monitoring system in a city, including the carbon footprint map (e.g., electricity, gas energy, etc.) and the new and renewable energy map (e.g., solar energy, geothermal energy, wind energy, etc.).
- *Part II:* Decision support system for the carbon emissions reduction for the building life cycle (i.e., optimal design technique, optimal construction management technique, and optimal operation and maintenance technique for minimizing the carbon emissions).
- *Part III:* Web-based carbon-integrated management system and smart-device-based real-time carbon-integrated management system.
- *Part IV:* Green-building policy in a city, including the incentive and penalty, sustainability rating system, and sustainability certificates.

The proposed system can be developed in the following three stages: (i) stage I from the planning & design phase through the construction phase; (ii) stage II from the operation & maintenance phase through the demolition & disposal phase; and (iii) stage III for the system integration and validation.

7.5. Implementing the building's dynamic operational rating as a diagnosing index

The operational rating, as a diagnosing index for evaluating the dynamic energy performance in the operation and maintenance phase of a given building, can be used for several purposes: (i) as a dynamic operational rating system for evaluating the current status of a building's dynamic energy performance; (ii) as a dynamic incentive and penalty program for encouraging all the building residents to voluntarily participate in the energy-saving campaign; and (iii) as a dynamic energy performance curve for managing the historical and future trends of a building's dynamic energy performance. Toward this end, the following considerations should be reflected [222–227].

- *Dynamic operational rating system:* In determining the category benchmark that is used as the standard index for assessing the energy performance of a given building, several factors should be considered, such as the building category, the region category, and the space unit size. The reasons for this are as follows. First, although two buildings are included in the same building category and the same region category, the energy performance of one building may differ from the energy performance of the other building due to their usage pattern

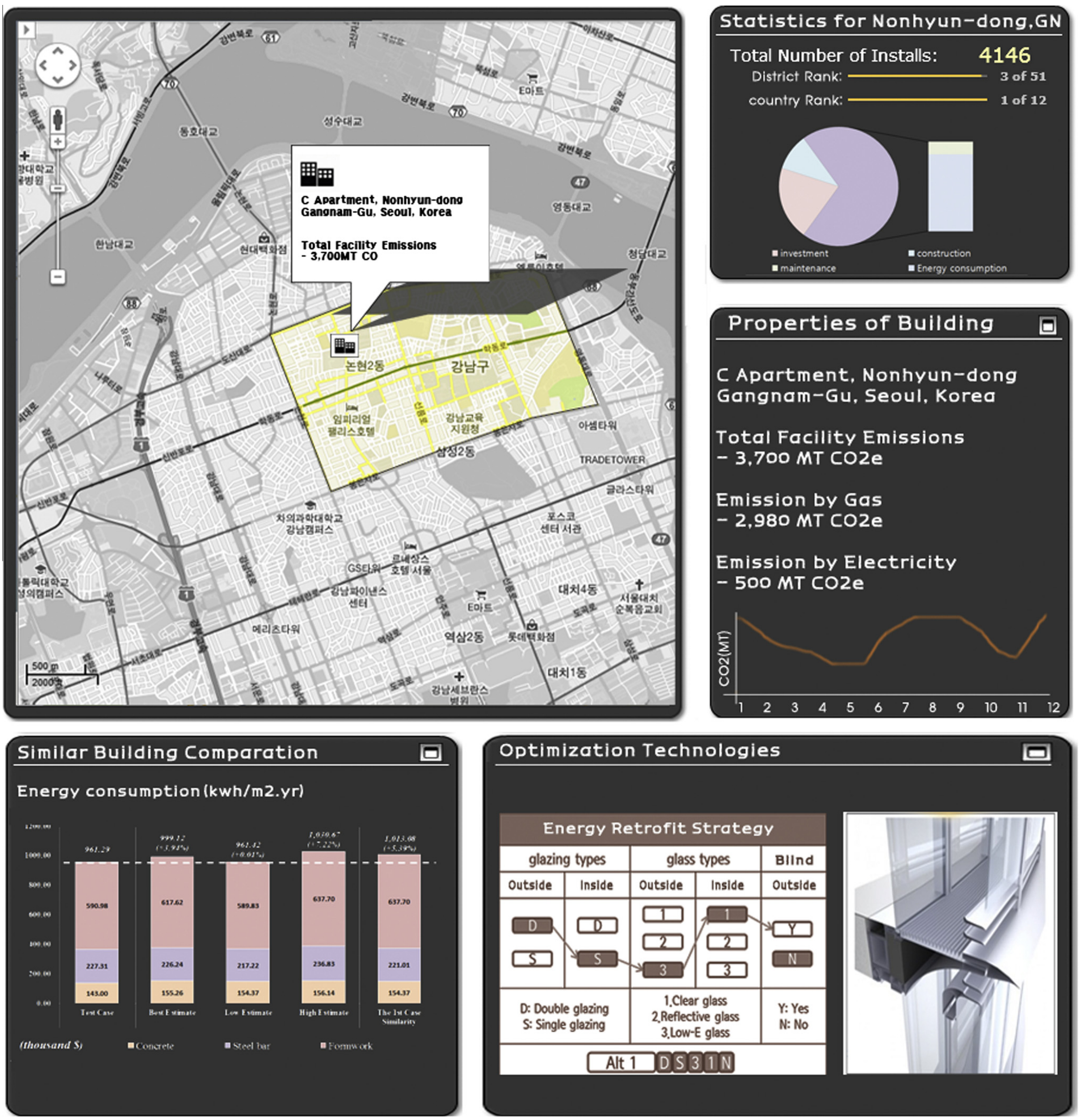

Fig. 14. Current status of a building's dynamic energy performance, its comparison values, and its energy retrofit strategy.

characteristics, such as the occupants' behavior, and the social and economic characteristics of the corresponding area. Second, if the negative correlation between the CO_2 emission density and the space unit size is not considered, the smaller the space unit size of a given building is, the lower the operational rating of the given facility. Therefore, the category benchmark should be established by considering the building category, the region category, and the space unit size so as to establish reasonable operational ratings of existing buildings(refer to Fig. 16) [11,14].

- *Dynamic incentive and penalty program:* To encourage the public to voluntarily participate in the energy-saving campaign, various types of comparison criteria should be provided, as follows: (i) for the building level, the averaging approach based on similar cases (e.g., maximum value, average value, and minimum value); (ii) for the community level, an operational rating that is one step higher than the grade of a given building; and (iii)for the national level, the operational rating as the minimum criteria for achieving the national carbon emissions reduction target. In addition, the actual value of a building's dynamic energy performance (i.e., the CO_2 emission density) should be provided with a visual chart so that the public would easily understand the operational ratings for a given building (refer to Fig. 17) [11,16].
- *Dynamic energy performance curve:* In managing the historical and future trends of a building's dynamic energy performance, the historical trends with regard to the energy performance of a given building during its "whole life cycle" should be provided

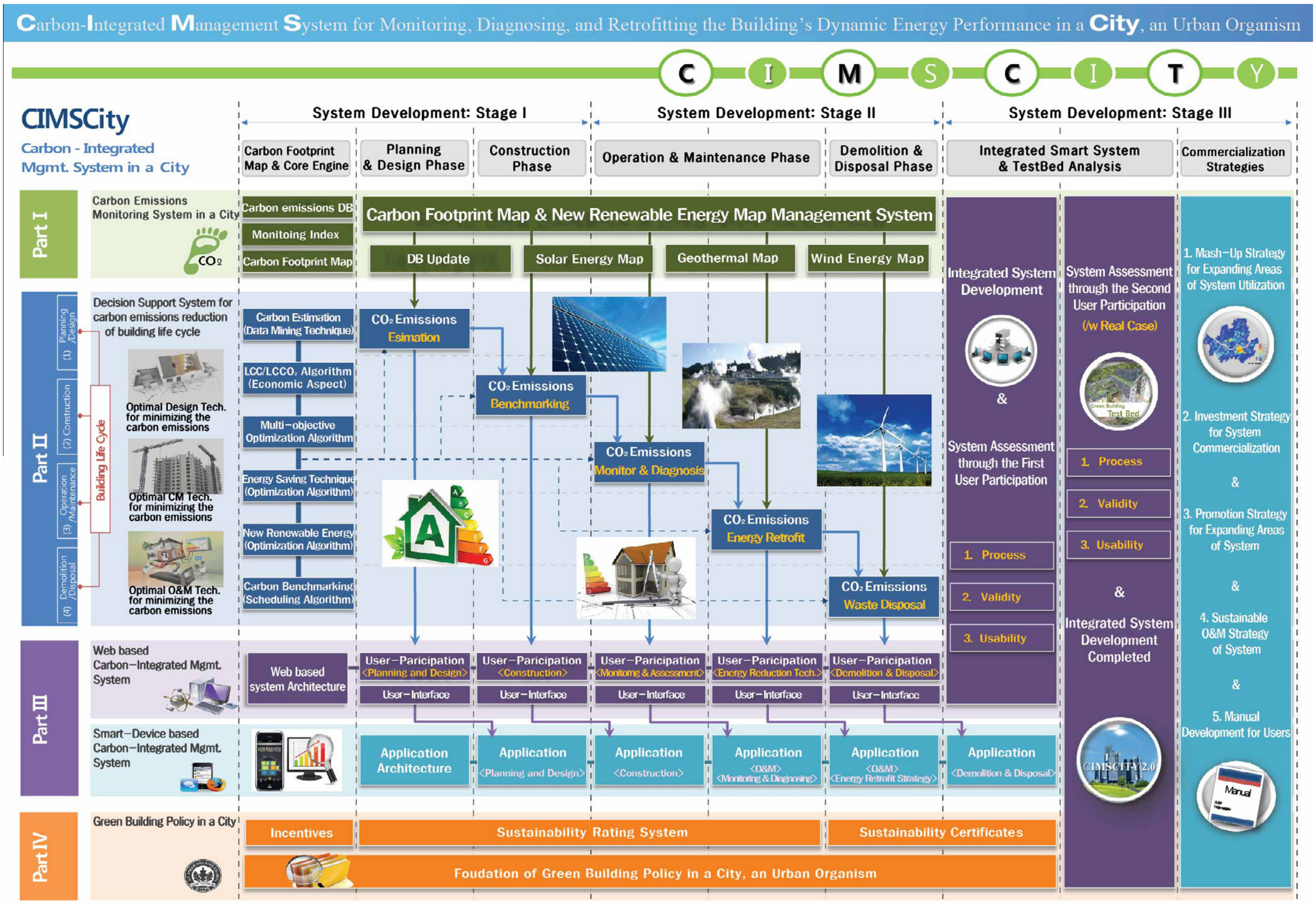

Fig. 15. Framework for the development of a carbon-integrated management system.

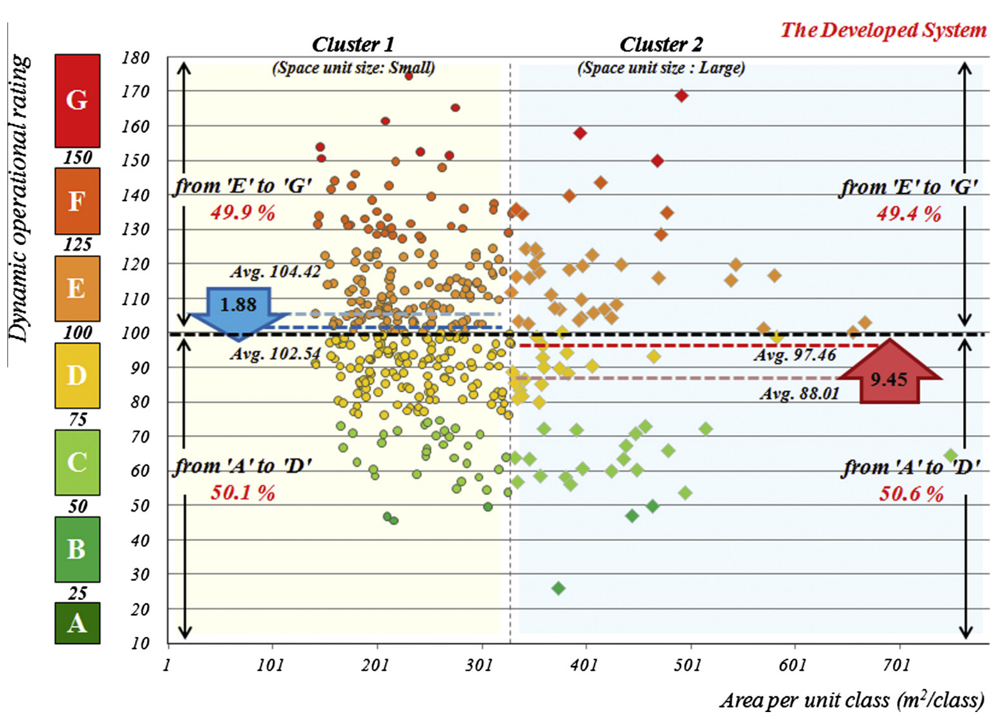

Fig. 16. Distribution of the dynamic operational rating by cluster in the developed system. *Source*: Koo and Hong [14] (License number: 3638220102635; License date: May 29, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Applied Energy. This is a License Agreement provided by Copyright Clearance Center (CCC)).

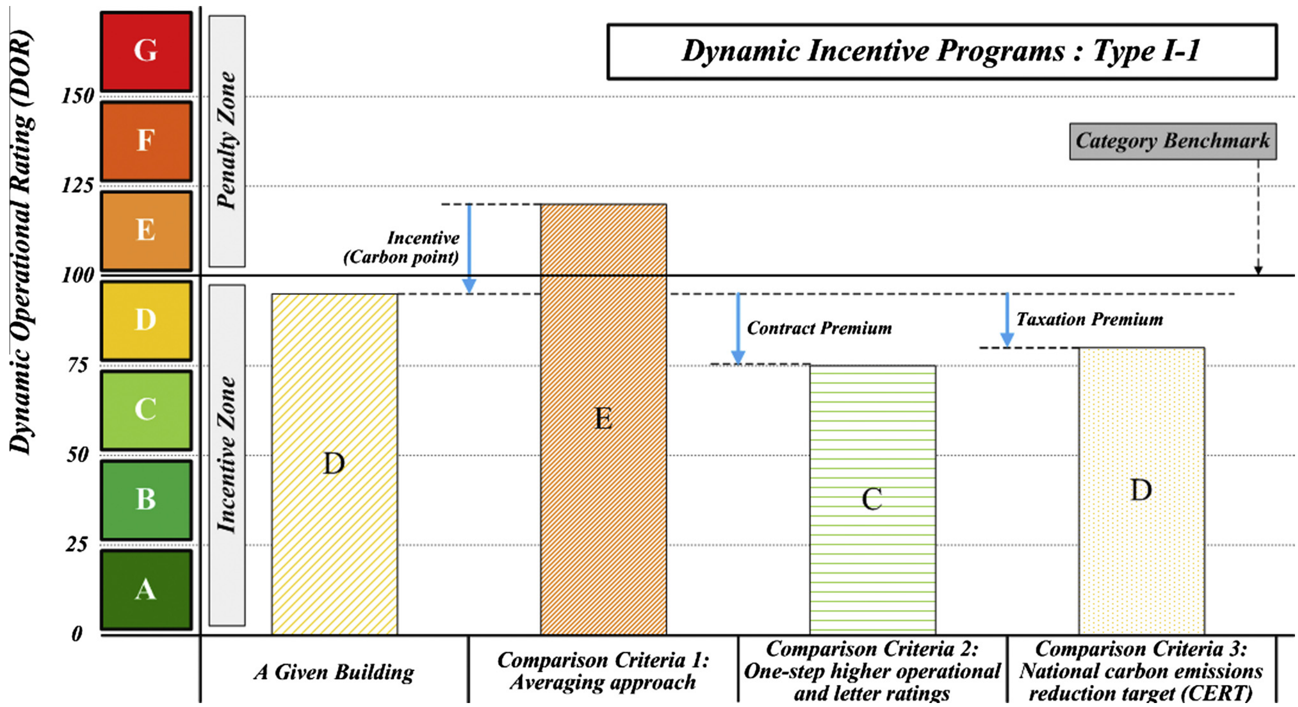

Fig. 17. Comparison chart for Type I-1 of the dynamic incentive programs [11,16].

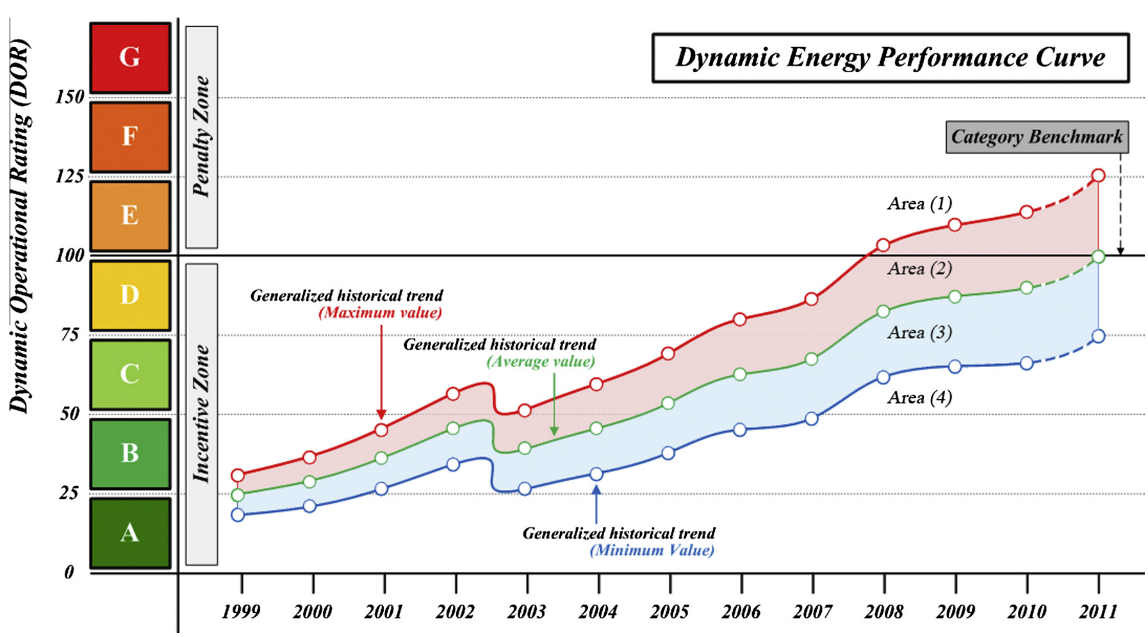

Fig. 18. Four types of dynamic energy performance curve. *Source*: Koo and Hong [17] (License number: 3610791499712; License date: April 16, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Energy and Buildings. This is a License Agreement provided by Copyright Clearance Center (CCC)).

so that the public would become fully aware of the overall historical trends. In addition, the "generalized historical trends" (i.e., maximum value, average value, and minimum value) should be provided as the comparative reference for the public to clearly recognize the relative positions of the historical trends in their building's dynamic energy performance (refer to Fig. 18) [11,17].

7.6. Estimating the operational rating using the energy performance of similar buildings

There are many previous studies on the performance gap between the asset rating system (mainly used in the design phase of new buildings) and the operational rating system (mainly used in the operation and maintenance phase of existing buildings)

[127–132]. This performance gap can occur due to both the usage pattern characteristics, such as the occupants' behavior, and the social and economic characteristics of the corresponding area. To overcome the performance gap, the following factors should be considered. First, except for the asset rating, which is based on the calculation method that considers the physical characteristics, a new approach should be considered in the design phase. That is, it is necessary to use the operational rating, which is based on the estimation method that considers the actual energy performances of similar buildings). For this estimation, the data mining or machine learning technique can be used. Second, the stochastic approach should be used to consider the uncertainty in estimating the operating rating in the design phase in advance. This approach can reduce the potential risk in the decision-making (i.e., the performance gap) (refer to Fig. 19) [15].

7.7. Implementing the multi-objective optimization process for establishing the optimal energy retrofit strategy

The optimal energy retrofit strategy depends on the project characteristics and the choices made by the decision-maker. First, to establish the optimal energy retrofit strategy, various factors should be considered, such as the project types (e.g., public, private, or public–private partnerships), project owners (e.g., public, private, or special-purpose entity), project delivery system (e.g., design-bid-build, design-build), project investment period, budget constraints, and available techniques (e.g., energy-saving techniques, new and renewable energy systems). Second, reflecting such factors, life cycle economic and environmental assessment can be conducted on each of the energy retrofit strategies. Accordingly, various performance indexes (i.e., initial investment cost, net present value as an absolute index, and savings-to-investment ratio as a relative index) can be calculated. Finally, the optimal energy retrofit strategy can be established by considering the aforementioned factors, but it is unrealistic to consider all the various performance indexes and the associated impact factors at the same time. Some previous studies used a few specific performance indexes to establish the optimal energy retrofit strategy [139,141,147,148,154,157,158,161,163,168–174,176–178,182,183,185,186,188,189,201,204,207] while other previous studies attempted to consider several performance indexes at the same time by applying multi-objective optimization [12,18,138,140,143–146,149–153,155,156,159,160,162,164–167,175,179–181,184,187,190–200,202,203,205,206,208].

To apply the concept of multi-objective optimization used in the previous studies to an actual project, the following limitations should be overcome. First, as most of the previous studies used complex equations in defining the fitness function to carry out multi-objective optimization, it is difficult for the user to understand and utilize the method. To solve this problem, the fitness function should be defined by a simple equation, and at the same time, such method should have excellent performance in determining the optimal solution [20,228,229]. As an example, Koo et al. [228] proposed the concept of the four types of fitness functions in multi-objective optimization. The final decision-makers can select the appropriate fitness function by considering the project characteristics. Specifically, all the alternatives can be standardized within the stated space. Also, the weight values can be found through the significance evaluation of each optimization objective. The '*weighted Euclidean distance*' can be used as shown in Eq. (1).

$$wEd_{x,b} = \sqrt{\sum_{i=1}^{n} w_i \times (x_i - b_i)^2}, \quad 0 \prec w_i \prec 1 \quad and \quad \sum_{i=i}^{n} w_i = 1 \qquad (1)$$

where $wEd_{x,b}$ stands for the weighted Euclidean distance between x and b; x_i stands for the value of the i-th measure; b_i stands for the corresponding benchmark value (0 or 1) for the value of x_i; and w_i stands for the weight value for the i-th measure.

Second, most of the previous studies focused on proposing the optimal solution in multi-objective optimization. The user, however, should be able to follow the process in which the optimal solution is determined, and to compare it with the other possible alternatives. To solve this problem, the visualized decision support tools can be used for analyzing the trade-off problems among the various performance indexes, and for determining the optimal

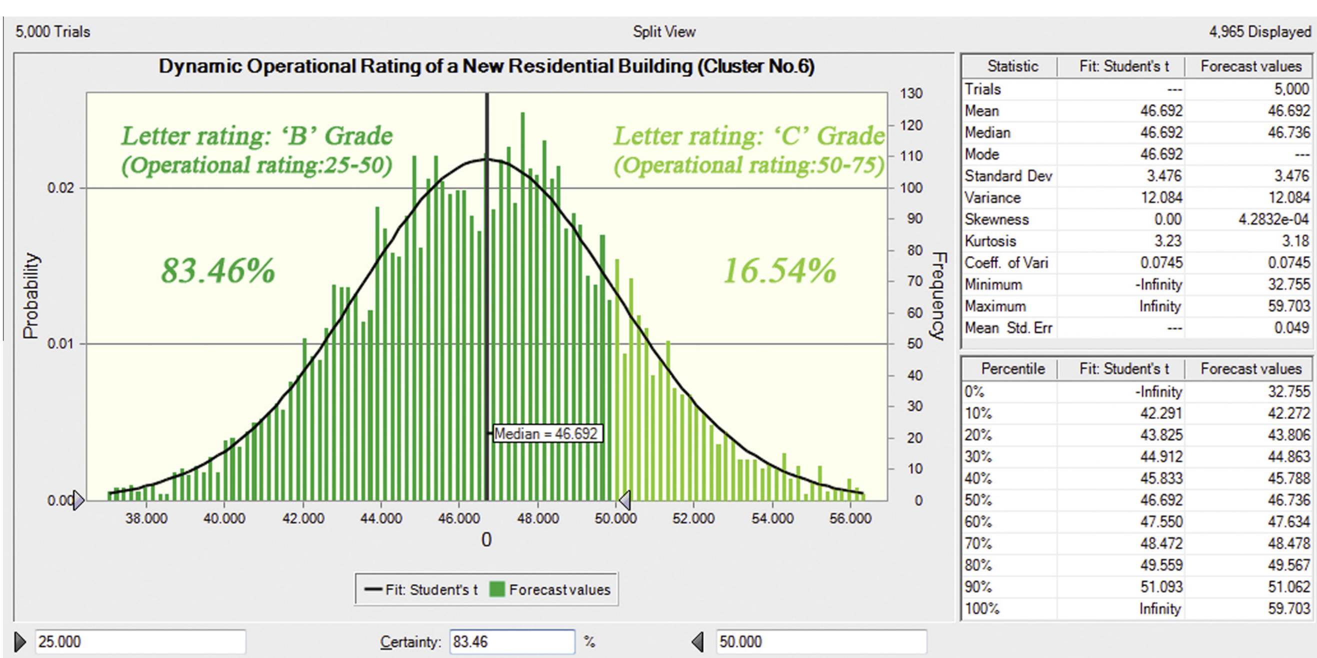

Fig. 19. Dynamic operational rating of a new building using the stochastic approach. *Source*: Hong et al. [15] (License number: 3638220598217; License date: May 29, 2015; Licensed content publisher: Elsevier; and Licensed content publication: Applied Energy. This is a License Agreement provided by Copyright Clearance Center (CCC)).

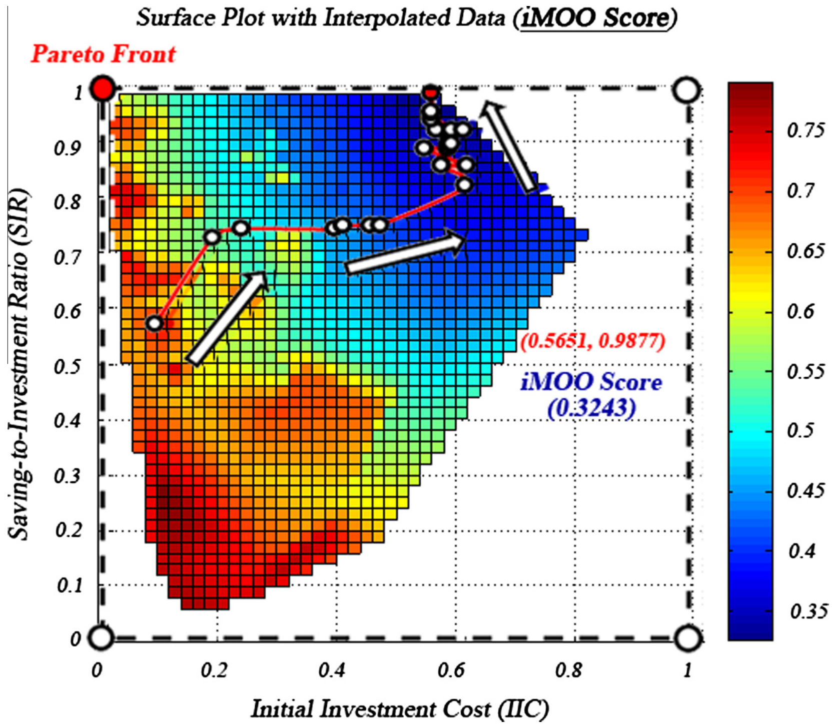

Fig. 20. Surface plot with the interpolated score (iMOO score) between the initial investment cost and the savings-to-investment ratio [11,20].

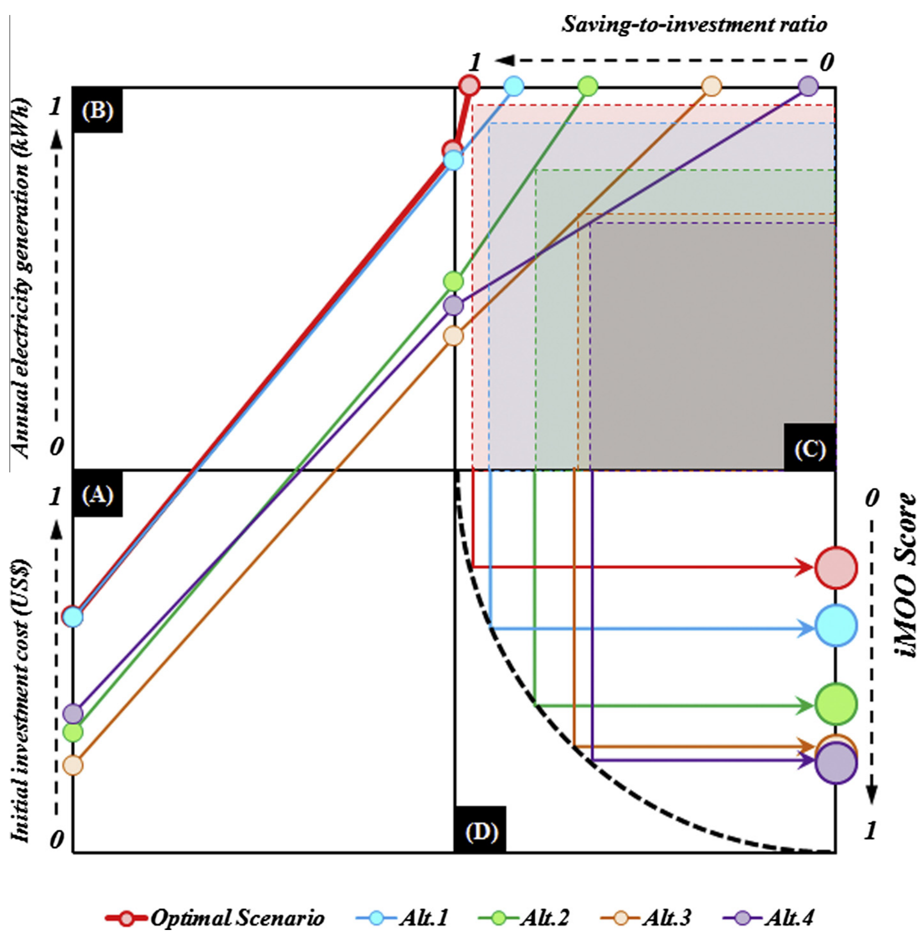

Fig. 21. Comparison chart for intuitive decision-making [11,20].

solution [20,229]. As an example, Fig. 20 shows the surface plot with the interpolated score (iMOO score) between the initial investment cost and the savings-to-investment ratio. This visualized decision support tool can be used for showing the optimization process to find the optimal solution in multi-objective optimization. In addition, Fig. 21 shows the comparison chart for intuitive decision-making. This visualized decision support tool can be used by the final decision-makers to compare the potential alternatives and to determine the optimal solution in multi-objective optimization.

7.8. Tracking the difference between the actual and estimated energy performances

Due to the deterioration of the existing buildings, the energy consumption in the building sector continues to increase. Accordingly, several studies are actively being conducted to analyze the effects of implementing energy retrofit strategies in real cases. As the initial investment costs required for the energy retrofit strategies are considerable, it is necessary to analyze the potential energy-saving effects of the energy retrofit strategies in advance. Despite such effort, there has been a difference between the estimated energy performance before the implementation of the energy retrofit strategy and the actual energy performance after the implementation of the energy retrofit strategy.

For example, in a photovoltaic system, a difference occurs between the estimated electricity generation and the actual electricity generation due to the various uncertainties, such as the climatic factors like the monthly average daily solar radiation, the pollutants on the surface of the photovoltaic system, the shading by the surrounding buildings or trees, or the simulation errors. Accordingly, it is necessary to consider all the uncertainties that cause power losses before implementing a photovoltaic system. It is unrealistic, however, to consider all the aforementioned uncertainties, and thus, the previous studies considered only some of the uncertainties. Therefore, there is a need to accumulate and establish a database by continuously tracking the difference between the estimated electricity generation and the actual electricity generation (or energy performance). Furthermore, by using such tracking information in implementing a photovoltaic system in the field, the electricity generation can be more accurately estimated, and the return on investment can be more accurately analyzed [230].

8. Conclusions

This study highlights the state-of-the-art in the major phases of a building's dynamic energy performance in terms of the sustainable construction management in the urban-based built environments (referred to as an ''*Urban Organism*'' in this study). Research in this area is very significant for the future of the building, energy, and environmental industries around the world. However, there is a lack of studies from the perspective of the dynamic approach and the system integration, and thus, this study was designed to fill the research gap. This study subdivided the major phases of a building's dynamic energy performance management into three phases (i.e., the monitoring, diagnosing, and retrofitting phases), and implemented the concept of ''*dynamic approach*'' to reflect the unexpected changes in the climate and energy environments as well as in the energy policies and technologies under the new paradigm of an ''*Urban Organism*''.

This study conducted an extensive literature review on the major phases of a building's dynamic energy performance (i.e., the monitoring, diagnosing, and retrofitting phases), focusing on the operation and maintenance phase. In addition, this study provided various illustrative examples of the building's dynamic energy performance management by phase so that the potential readers could better understand the application in the previous studies.

Based on the extensive literature review, this study suggests the specific future developments and challenges by phase (i.e., the monitoring, diagnosing, and retrofitting phases) from the following eight viewpoints: (i) integrating the monitoring phase into the diagnosing and retrofitting phases; (ii) visualizing a building's dynamic energy performance using real-time data; (iii) retrieving valuable information from the big data in a large city; (iv) developing a carbon-integrated management system as a large complex system; (v) implementing the building's dynamic operational rating as a diagnosing index; (vi) estimating the operational rating using the energy performance of similar buildings; (vii) implementing the multi-objective optimization process for establishing the optimal energy retrofit strategy; (viii) tracking the difference between the actual and estimated energy performances. These research items are in line with the sustainable construction management strategies for systematically controlling a building's dynamic energy performance, which can be finally related to the system integration for the development of a carbon-integrated management system as a large complex system in terms of an ''*Urban Organism*''.

It is expected that this study will allow researchers, practitioners, and policymakers to understand the dynamic approach for maintaining the building's energy performance and to adopt the holistic approach for developing a *Carbon Integrated Management System for monitoring, diagnosing and retrofitting the building's dynamic energy performance in a City, an urban organism (CIMS*City) so as to minimize the carbon emissions in the operation and maintenance phase of the building sector.

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