Sensors and Materials, Vol. 37, No. 4 (2025) 1615–1638
MYU Tokyo

S & M 4009

Development of a Location-based Rapid Building Performance Simulation Tool Combined with Design of Experiment Method for Energy Efficiency Enhancement in Existing Healthcare Building Retrofitting

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(Received September 8, 2024; accepted April 11, 2025)

Keywords: net-zero carbon emission, healthcare building, building performance simulation tool, design of experiment

In this study, we address the critical challenge of enhancing energy efficiency in existing long-term care centers in Taiwan, aligning with the nation's 2050 net-zero emissions goal while accommodating an aging population. We present a novel framework integrating the Building Energy Simulation and Analysis platform (BESTAI), a user-friendly building performance simulation tool, with JMP software for experimental design and statistical analysis. The methodology was applied to a case study of a typical Tier C long-term care facility in southern Taiwan. BESTAI demonstrated high accuracy with a deviation of less than 3% from metered energy consumption. Four key factors were investigated: air conditioning efficiency, window-to-wall ratio, window *U-value*, and shading coefficient. The comparative analysis of full factorial, Taguchi, definitive screening design (DSD), and custom design experimental methods revealed that air conditioning efficiency and window shading coefficient were the most significant factors affecting building energy consumption. The DSD and Taguchi methods proved to be the most cost-effective, requiring only 11 and 9 trials, respectively, to achieve optimal solutions, compared with 81 trials for full factorial design. Regression models consistently identified the air conditioning system's coefficient of performance as the most influential factor. The optimized configuration achieved a 47% reduction in electricity usage. This research provides a replicable model for rapid, accurate building energy analysis and optimization, which is crucial for Taiwan's sustainable development in the face of climate change and demographic shifts. The findings offer valuable insights for policymakers and building managers in prioritizing energy efficiency measures in the long-term care sector. Future research can enhance this study's optimization framework through sensor technology integration. Smart sensors can validate BESTAI simulation results in real time, with temperature and humidity sensors verifying heating, ventilation and air conditioning (HVAC) performance, occupancy sensors capturing usage patterns for demand-based control, and IoT power meters providing equipment-level

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https://doi.org/10.18494/SAM5364

ISSN 0914-4935
https://myukk.org/

consumption data. Thermographic imaging systems can monitor building envelope performance. This sensor-integrated approach can create a feedback loop between simulation predictions and actual performance metrics, enabling the continuous optimization of energy-saving strategies in long-term care facilities.

1. Introduction

The Industrial Revolution in the 1800s was propelled by coal, petroleum, and natural gas as critical energy sources. Coal and fossil fuels have since become the dominant global sources of energy; during the 1950s, coal and fossil fuels accounted for more than 70% of global electricity generation.(1) However, the emission of greenhouse gases from the burning of biofuels has contributed to the increase in Earth's surface temperature and led to climate change. Espousing such estimate, the Sixth Assessment Report of the United Nations Intergovernmental Panel on Climate Change released in February of 2022 noted that global climate hazards are likely to occur over the next two decades if the average temperature increases to 1.5 °C above pre-industrial levels.(2) According to the World Meteorological Organization, the global mean near-surface temperature in 2023 was 1.45 ± 0.12 °C above the pre-industrial 1850–1900 average.(3) The abovementioned reports underscore the importance of reaching net-zero emissions, which is integral to sustainable development as well as critical to limiting the destructive forces brought on by extreme weather events.

Achieving net-zero global carbon dioxide (CO_2) emissions by 2050 has reached worldwide consensus; many countries have established different carbon neutrality timelines while maintaining economic growth.(4) It is important to note that reaching net-zero emissions requires efforts from all industries. The International Energy Agency (IEA) pointed out that more than 85% of buildings should be zero-carbon-ready.(5) Taiwan has undertaken its net-zero building transformation by adopting concepts outlined by the IEA, EU, US, and Japan. By 2050 (Fig. 1), 100% of Taiwan's new buildings will be zero-carbon-ready, with more than 85% of existing structures being nearly zero-emission buildings.(6) Renovating existing private buildings relies on protecting ownership rights and providing incentives and subsidies, while state-owned buildings rely on timely enforcement. Furthermore, investment and research should be devoted to developing novel building energy-saving approaches, as well as carbon reduction technologies.

Common strategies for achieving net-zero carbon buildings encompass enhancements in the thermal insulation of building envelopes, improvements in equipment energy efficiency, the adoption of smart energy management systems, and the integration of additional renewable energy sources. Energy-saving technologies for building envelopes are well-established today, especially in their comprehensive application in passive buildings.(7) This encompasses various components such as roofs, doors, windows, and walls, each with its applicable technologies. For instance, advanced energy-efficient roofs include modern green roofs, photovoltaic roofs, and radiation-penetrating barriers. The application of phase-change materials in building walls enhances thermal mass effects, providing an energy-efficient solution for environments with significant day–night temperature fluctuations. Different window types also yield varying energy-saving effects, which can be evaluated using building performance simulation tools.

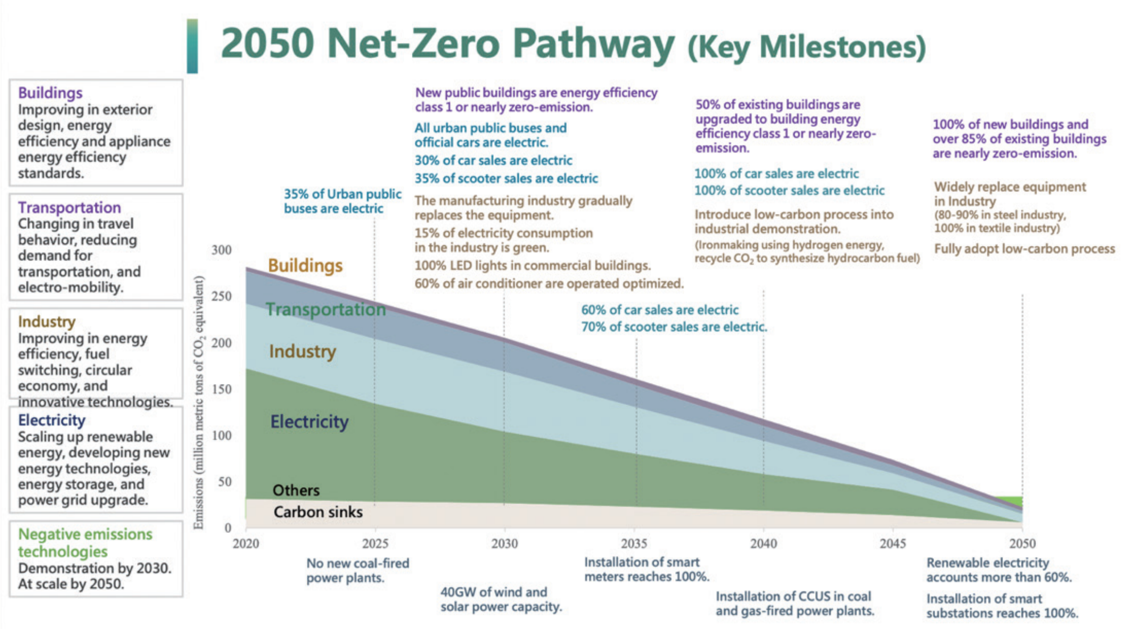

Fig. 1. (Color online) Taiwan's pathway to net-zero emissions in 2050.

On the other hand, Taiwan is concurrently grappling with the challenges of an aging population and declining birth rates. Taiwan officially entered the aging society in 2018 and is on course to become a hyper-aged society by 2026 (Fig. 2). This has brought about a corresponding rise in the number of people who need long-term care. However, the shifts in family structure have led to a reduction in the number of caregivers within the family unit. The average fertility rate in Taiwan is 1.18 persons, and the number of members per household stands at 2.77 persons. To adapt to this enormous need and mitigate the burden of family caregivers, the Taiwanese government launched the 10-year Long-term Care Plan 2.0 in 2017. One of the goals of saving-engaging these policy goals is "aging in place." To provide the public with integrated, flexible, and convenient care services close to home, a three-tier system consisting of community-based integrated service centers (Tier A), combined service centers (Tier B), and long-term care stations in alleys and lanes (Tier C) is established in this plan.[(8)]

In 2022, a total of 680 Tier A, 6852 Tier B, and 3686 Tier C centers were established. However, the design development of long-term care buildings in Taiwan has traditionally prioritized creating accessible spaces, with limited attention given to improving the living environment and energy usage for the elderly. Consequently, with the rapid changes in demographic structure and the increasing number of long-term care centers, it is crucial to create comfortable living environments tailored to the characteristics of elderly users and simultaneously reduce energy consumption to achieve energy efficiency. This is particularly relevant to the quality of care for the aging population.

BPS tools have become a popular way to support the design decisions of architects or engineers in various stages of energy-efficient buildings. These instruments first build up an energy model, with inputs for local weather, building geometry, building envelope

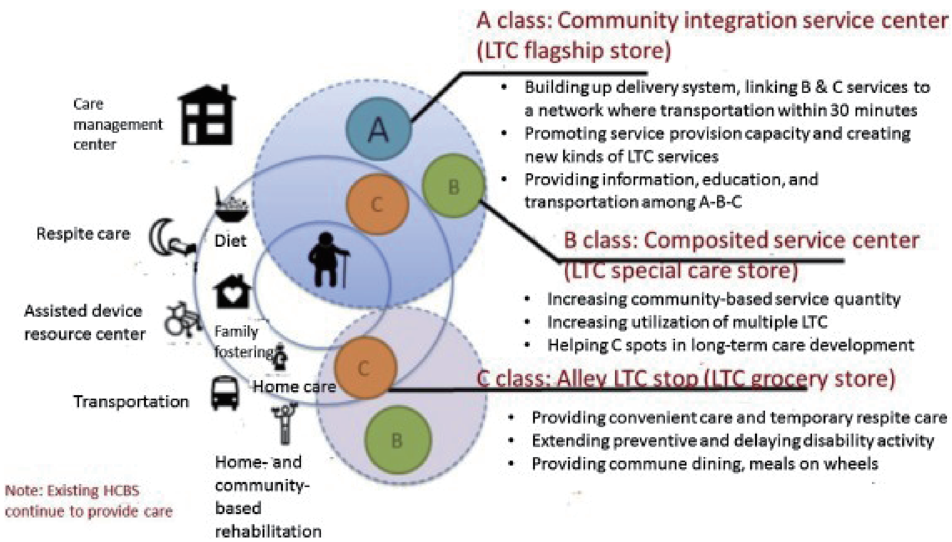

Fig. 2. (Color online) ABC HCBS network design.

characteristics, internal heat gains from lighting, people, and plug loads, heating, ventilation and air conditioning (HVAC) system specifications, operation schedules, and control strategies. Next, mathematical models are used to depict building systems and their interactions in order to calculate thermal loads, system responses to those loads, and holistic energy use, along with related metrics such as occupant thermal comfort, energy use, and carbon emissions. On the basis of a referencing book review,[9] an overview of BPS tools indicates that the current fourth-generation tools tend to be fully integrated concerning different aspects of building performance, with new developments concerned with intelligent knowledge-based user interfaces, application quality control, and user training. These approved programs, which are applied to the green building rating system in the Leadership in Energy and Environmental Design (LEED), have at least ten programs among them.[10] These program tools were, moreover, widely used in the United States and include DesignBuilder, DOE-2, eQuest, Ecotect, Energy-10, Green Building Studio HEED, and IES VE. Among these, Ecotect, Energy-10, and eQUEST are often used in academia.[11] On the other hand, IES VE, DesignBuilder, and Ecotect are popular commercially available simulation tools that are widely used among architects.[12]

Developed in 1996, EnergyPlus was one of the best-known energy simulation software tools. It has become a tool used to evaluate building energy performance and is highly recommended by the U.S. DOE.[13] The development of EnergyPlus allowed the Building Loads Analysis and System Thermodynamics (BLAST) to integrate mutual functions with the DOE-2 in 1998. It is DOE's open-source whole-building energy modeling (BEM) engine, the successor to DOE-2.1E. EnergyPlus embodies state-of-the-art BEM knowledge in a comprehensive and robust engine that is continuously maintained, thoroughly documented, and fully supported. Thus far, it has been most widely used according to the annual growth of global users (shown in Fig. 3). However, the lack of a free comprehensive graphical user interface (GUI) has prevented EnergyPlus from becoming widely adopted by practitioners.[14] The release of other GUI editors,

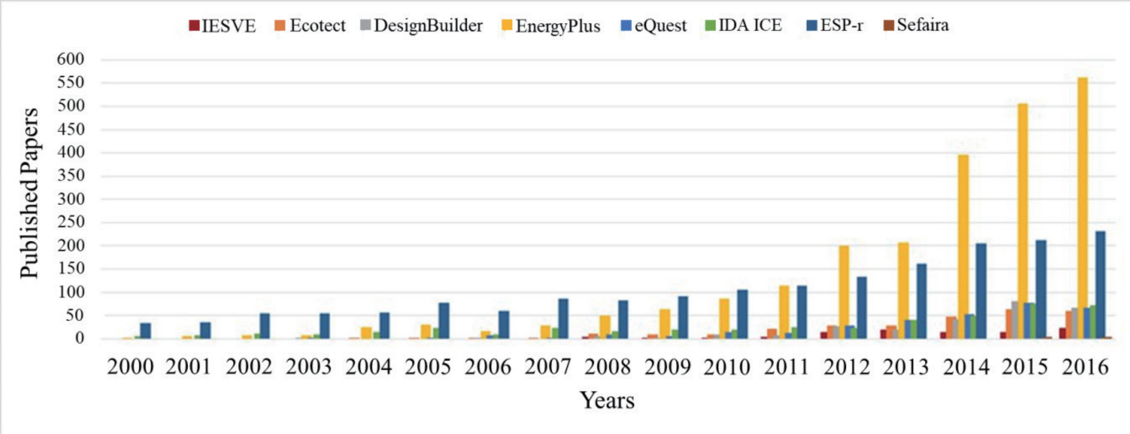

Fig. 3. (Color online) Statistical quantity for using building performance tools as published in academic journals.

such as IDF editor, DesignBuilder, Comfen, OpenStudio, Simergy, Sefaira, DIVA, and AECOsim, can simplify the building model assembly process for energy simulation to make EnergyPlus accessible to architects and other professionals.

Existing studies aimed to identify executed criteria and requirements of BPS tools, as well as rank and compare BPS tools, have been conducted over the past two decades. Hong *et al.* set up a decision-making system to select a BPS tool and suggested four selection criteria, namely, computing capability, usability, data exchange capability, and database support.(15) Attia *et al.* identified architects' and engineers' requirements and selection criteria for BPS tools; their research indicated that architects prioritized the integration of intelligent design knowledge based on five criteria.(12) On the other hand, engineers agreed to prioritize the accuracy of tools and the ability to simulate detailed and complex building components. The developers of the BPS tool can use the survey results to improve or create a BPS tool.

Note that some buildings require systemic improvement to reach optimal energy conservation. BPS is not easy to use because it requires professionals in engineering professions who are familiar with energy performance diagnosis. Therefore, in this study, we aim to integrate an appropriate BPS tool along with experimental design and statistical analysis to create an easy-to-operate platform. The application of this platform should yield varying strategies specific to the building under analysis.

2. Methodology

In this study, we propose an integrated platform to implement the existing building improvement program. In this proposed platform, Building Energy Simulation and Analysis platform (BESTAI) was adopted to conduct simulations of energy consumption in the existing building. BESTAI has an integrated GUI suitable for conducting an EnergyPlus building energy consumption analysis. Considering that those who use statistical software in the field of architecture may not be well-versed in statistics, our research adopts JMP to perform the necessary statistical analysis because it can generate optimal building energy-efficiency improvement plans visually, which would otherwise be overlooked when presented in numbers.

Figure 4 outlines the steps required to implement the existing building energy-saving improvement program. First, a target structure needs to be ascertained at Step A, and relevant information is collected, which may include but are not limited to the building location and orientation, the number of floor levels, building material, and electrical equipment. Obtaining a building's past electrical record is also critical because such data can be used to verify simulation results. The more comprehensive the data collection process, the more accurate the building energy modeling will be. In Step C, the accuracy evaluation of the proposed BPS tool needs to be conducted on the basis of the building's existing power usage. The fourth step involves the JMP software, which is used to execute the experimental design; BESTAI is then used to simulate the energy consumption of various experimental conditions, and the main factors for building energy consumption can be determined. Finally, the JMP software is used to obtain the optimized energy-saving improvement plan.

2.1 BESTAI

The methodology employed in the development and implementation of BESTAI, a web-based building energy simulation and optimization tool, is designed to address the specific needs of the Taiwanese built environment. BESTAI utilizes a client-based web application architecture, enabling users to access the system via various devices, including computers, laptops, and

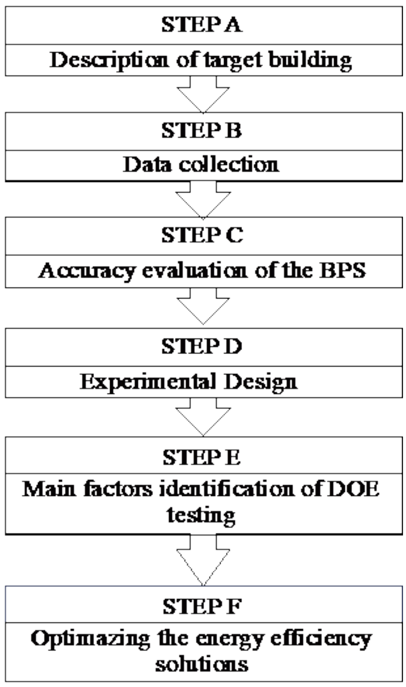

Fig. 4. Schematic of proposed building energy consumption optimization program.

mobile devices. This architecture facilitates real-time building simulation analysis, the optimization of energy consumption for existing buildings in Taiwan, and customized analysis and reporting functions. A key methodological component of BESTAI is its extensive set of preassembled parameters, which are organized into editable and exchangeable libraries. These libraries cover four main areas: location-specific data for Taiwan, HVAC equipment specifications, building materials and assembly templates, and energy-efficient product data aligned with Taiwan's Energy Label Program. The system incorporates two primary simulation methodologies. The first is a rapid modeling analysis, which employs a simplified modeling interface for quick analysis. Users input basic building information through a web-based interface and specify internal load settings, including air conditioning, lighting equipment, and scheduling operations, and the system performs real-time simulations based on these inputs. The second method is Input Data File (IDF) simulation, which allows for a more detailed analysis by enabling users to directly upload building model files (IDFs) and climate files (EnergyPlus Weather Files), utilizing cloud-based high-speed computing services for simulation. The user interface is designed for accessibility and ease of use, featuring a web-based spreadsheet application for data input, a Chinese language interface to remove language barriers for Taiwanese users, and a mobile-responsive design for smartphone access. BESTAI's analysis and reporting methodology includes Return on investment (ROI) assessment, annual energy consumption calculation, and electricity bill estimation, with reports generated automatically based on simulation results. The implementation process follows a structured approach, beginning with user authentication, followed by the input of building information (including name, the number of floors, orientation, space dimensions, and window-to-wall ratios), the selection of parameters (such as building façade, internal loads, operational schedules, HVAC equipment, and climate zone), simulation execution, and finally, the generation and presentation of results. This comprehensive methodological approach enables a rapid, accessible, and context-specific building energy analysis tailored to the unique characteristics of Taiwan's built environment. The combination of comprehensive preset libraries, user-friendly interface, and cloud-based simulation capabilities distinguishes BESTAI as an efficient tool for building energy optimization in Taiwan, allowing users to perform complex analyses without the need for high-performance computing equipment or extensive technical expertise.

2.2 Statistic and analytic tool

From the 1920s, when the breeding scientist Ronald Fisher first introduced the concept of Design of Experiments (DOE) in agricultural experiments, DOE has undergone a century of development and has found wide-ranging applications in both academia and industry. In the context of building energy efficiency, DOE has been utilized in the literature. For instance, according to Filfli's 2006 study,(16) this method was employed to reduce traditional building energy consumption. To further apply the DOE methodology to achieve low-energy buildings, Chlela *et al.* used it to enhance the energy efficiency of office buildings.(17) In their research, a partial factorial design based on the Taguchi method was adopted. Process variables of interest included characteristics of the building envelope structure, indoor lighting heat gains, and nighttime ventilation, while the response variable was energy consumption. The empirical model established in the study quantified the impact of each factor on the final energy consumption of office buildings and identified the factor settings that minimized energy consumption. In recent years, Jankovic *et al.*[18] have conducted research using various DOE methods to identify the main effects and interaction factors affecting the overall thermal performance of building façades. They transformed the conclusions from different DOE responses into a universal decision tree, providing recommendations for selecting the optimal DOE, thereby significantly reducing the number of experimental designs required.

JMP is a powerful statistical analysis program with interactive data visualization capabilities. It originally stood for "John's Macintosh Project"[19] and was first released in October 1989. It empowers scientists and engineers to explore data visually.[20] JMP enables researchers to perform a wide range of statistical analyses and modeling, such as creating interactive graphs and charts, discovering patterns of variation across many variables at once, and developing powerful statistical models.[2] It was used mostly by scientists and engineers for the DOE.

2.3 Experimental design for improving building energy consumption

A designed experiment is a controlled set of tests designed to model and explore the relationship between factors and one or more responses. JMP includes a variety of methods, such as full factorial, Taguchi, screening, response surface, definitive screening design (DSD), and custom design (CD), which enable energy auditors to create efficient experimental designs that work for their situation. JMP has a prediction profiler feature, which allows for accurate predictions without the use of data yielded from actual experiments. Thus, the user can directly render the response surface using one input factor, X, and one output response, Y. The higher the number of factors and responses, the more difficult it is to predict. Figure 5 is an example of the JMP prediction profile, which is based on an existing building that uses the Taguchi experimental

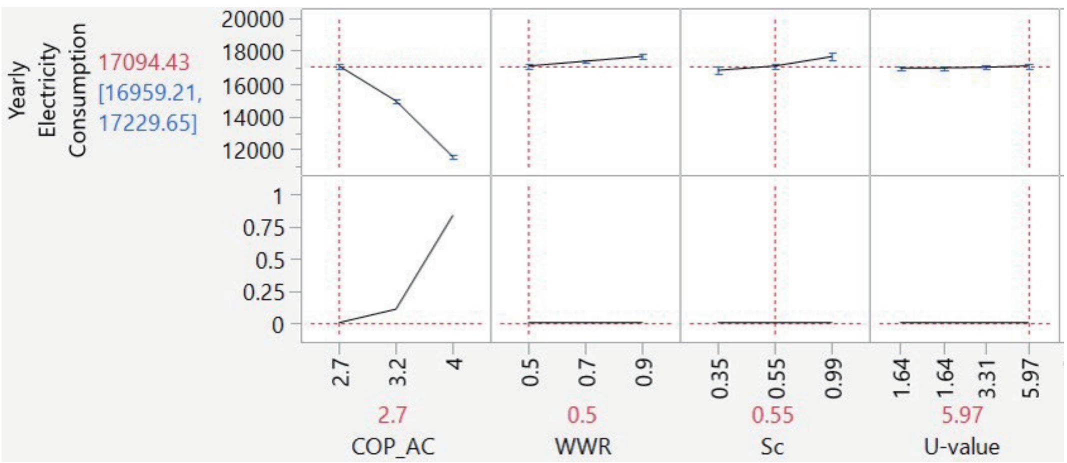

Fig. 5. (Color online) Example of the JMP prediction profile of the annual energy consumption response of buildings with different combinations of factors.

design method to obtain a combination of nine factors. The annual power consumption of the building simulated by BESTAI is input into the JMP software. Users can adjust parameters accordingly (e.g., COP_AC is changed from 2.7 to 4.0), and the predicted response value (e.g., annual power consumption) can be obtained in time.

The factors affecting building energy consumption range from the structure's exterior to the installed indoor electrical equipment. Walls, roofs, windows, lighting, and air-conditioning systems are also influential. However, not all owners have the resources to make improvements. Therefore, it is essential to identify how the aforementioned factors may interact with one another in an experimental setting so that an improvement proposal can be proposed accordingly. The computing capabilities of JMP yield high estimate accuracy, but it also provides the optimal combination of response factors even when DOE is scaled down.

3. Case Study

In this case study, the selected long-term care building for evaluation is located in downtown Kaohsiung, an area with extremely high real estate values. This building is representative of typical Tier C long-term care buildings in Taiwan, thereby presenting an exemplary retrofitting case study for potential wide applications in the Taiwanese context.

Retrofitting this Tier C long-term care building faces challenges owing to its climate and site conditions, which are characterized by dynamic and variable weather patterns in a humid subtropical climate. The location of the building is situated just above 22.4° north latitude, slightly south of the Tropic of Cancer in Kaohsiung, Taiwan. This region experiences temperatures ranging from an average low of 10 °C (50 °F) in January to an average high of 33 °C (91 °F) in July, with a consistent daytime length throughout the year—approximately 13.5 h of daylight on the summer solstice and 10.5 h on the winter solstice. With over 2210 h of bright sunshine, the city is among the sunniest areas in Taiwan. The noon temperature reaches 35 °C in summer and 25 °C in winter. The high summer sun angles underscore the necessity for a sheltering roof to control light levels, solar gains, and indoor temperatures. Despite enjoying about 225 bright sunny days per year, there is still a monthly rhythm of overcast or rainy days, including an average of two to three typhoons per month during the summer. The annual mean solar irradiation and precipitation are 3896 MJ/m^2 and 1968.2 mm, respectively.

According to the proposed framework, the standard operating procedure for assessing energy efficiency improvements in this Tier C long-term care building is outlined as follows:

Step A: Description of target building

Tier C: Long-term care stations around the blocks are designed to offer respite services in the neighborhood and implement primary prevention programs, including social participation, health promotion, communal dining services, as well as preventive and disability-delaying services. To comply with the regulations for accessible spaces, the majority of Tier C long-term care stations are located on the ground floor of buildings. Therefore, a building of this type is selected in the case study to explore a retrofitting approach to improve its energy efficiency.

As shown in Fig. 6, this existing building facing east–south is a 13.45-m-tall reinforced concrete structure comprising four floors, with an arcade extending from the roof to the ground floor with a window-to-wall ratio of 90% on the ground floor. This large window-to-wall ratio design ensures an even distribution of natural light. However, it leads to a strong greenhouse effect throughout the day. This building has a rectangular floor plan of 9.01 m length and 3.97 m width (Fig. 7). The area of each floor is about 35.77 m^2 and the floor-to-ceiling height of each story is 3.3 m. The care activity space for the elderly in this station is 18.71 m^2.

The ground floor of this building serves as a Tier C long-term care station. From Monday to Friday, between nine a.m. and five p.m., healthy or sub-healthy elderly individuals engage in rehabilitation sessions and social activities and have lunch and dinner at this station. Two staff members are responsible for the day-to-day operations of the Tier C long-term care station, and there is one external teacher for each hourly session. The staff's working hours are from eight a.m. to six p.m. The maximum capacity for elderly individuals is 15 people.

Step B: Data collection

The initial task in this step is to identify the energy sources and uses of the target station. In this case study, the primary energy source is electricity. A successful energy efficiency retrofitting plan in the existing Tier C station relies on accurate and appropriate data to develop a profile of its energy situation. Utility bills are typically the first consideration and the most easily collected data. The monthly electricity consumption of this target station is shown in Fig. 8. The annual energy consumption of this Tier C station is 411.02 kWh/(m^2·a). The peak electricity consumption primarily occurred during the air conditioning period in the summer months of July and August when the air conditioners operated for extended periods, resulting in substantial electricity consumption. Throughout the remaining transitional periods, electricity consumption was primarily attributed to lighting systems and electrical equipment.

Fig. 6. (Color online) Building appearance of a long-term care station façade facing east–south.

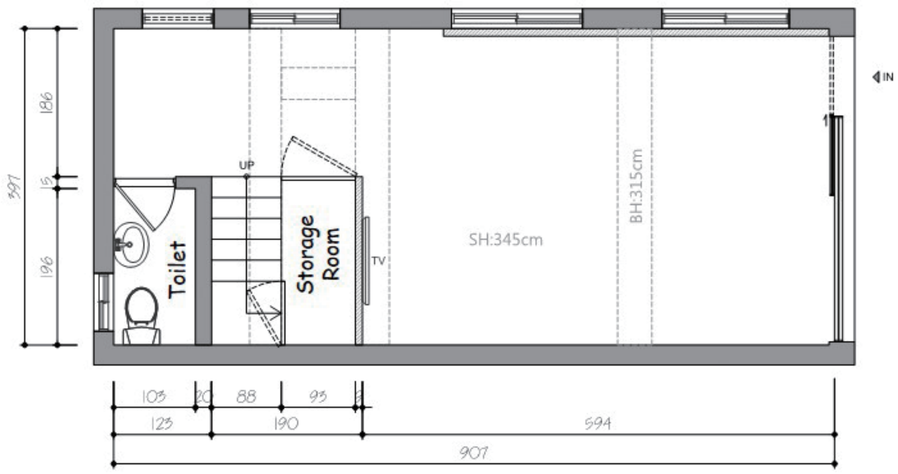

Fig. 7. Floor plan of long-term care station.

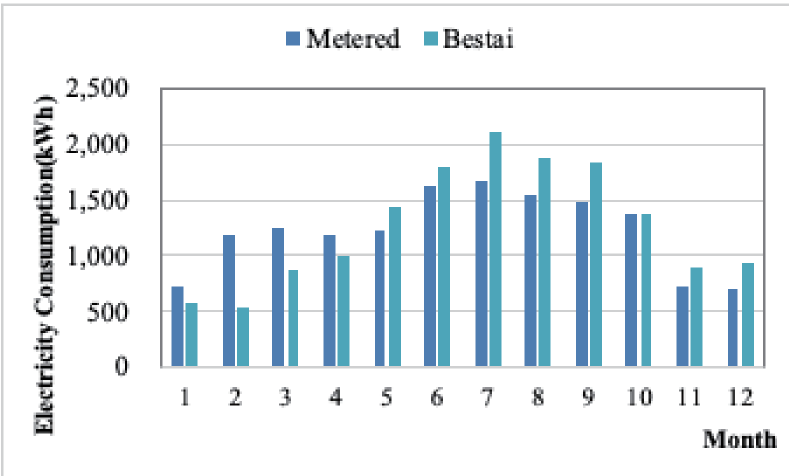

Fig. 8. (Color online) Comparison of monthly electricity consumption with metered and simulated tools.

Subsequently, concerning energy uses, we should identify the equipment and systems that consume the majority of energy in this target station. After an on-site inventory, this target station is equipped with a 7.4 kW split-type air conditioner, a refrigerator (180 W), a water dispenser (500 W), a desktop computer (200 W), a laser printer (430 W), a 70-inch LED television (90 W), and a broadcasting system (500 W).

For computer simulation and modeling, the physical parameters include the window, the external wall structure, and the window-to-wall ratio. The number of occupants, the heat gain of appliances, and the lighting for each floor are listed in Table 1. Generally, the air conditioner, lighting equipment, computer, and appliances in this Tier C station have identical operating periods corresponding to the staff's work shifts from eight a.m. to six p.m.

Table 1
Physical parameters for long-term care building.

Parameters	Values
U-value @ exterior wall	3.495 W/m^{2}K
U-value @ roof	1.0 W/m^{2}K
Window-to-wall Ratio	0.9 (façade)
U-value @ window	5.5 W/m^{2}K
Clear glass	*U* = 5.97 W/m^{2}K, *SHGC* = 0.83, *Visible light transmittance* = 0.88
No. of people	1st Floor: 2 staff (8 a.m.–6 p.m.) + 15 persons/h (9 a.m.–5 p.m.)
Lighting	1st Floor: 660 W (10 W/m^2)
Appliance	1st Floor: 1900 W

Step C: Accuracy evaluation of BPS tool

The accuracy and efficiency of the BESTAI building performance simulation (BPS) tool were evaluated through a comprehensive analysis of its performance against actual energy consumption data. The results demonstrate the tool's high accuracy and time efficiency, positioning it as a valuable asset for rapid building energy modeling and optimization in Taiwan.

Weather data play a crucial role in building energy simulation. In this study, we utilized the latest typical meteorological years (TMY3) data for Taiwan, provided by the Architecture and Building Research Institute (ABRI).(21) This dataset, sampling 15 standard years from 1998 to 2012, ensures that the simulations are based on reliable and representative climatic conditions. The ability of BESTAI to automatically generate power consumption analyses based on user-selected locations significantly streamlines the simulation process. Our accuracy evaluation revealed that BESTAI's estimations fall within a 5% margin of error when compared with actual utility bills (Fig. 8). This high level of accuracy is particularly noteworthy given the complexity of building energy systems and the variability in user behavior. The breakdown of simulated electricity consumption provided valuable insights into the energy use patterns of the studied building. Air conditioners accounted for 20% of the total consumption, lighting systems accounted for 19%, and personal computers (PCs) and electric appliances accounted for a substantial 61%. This distribution highlights the significant impact of office equipment on overall energy consumption, a finding that can inform energy-saving strategies in similar buildings. The consistency in monthly electricity demand, particularly for PCs and electric appliances, suggests a relatively stable baseline energy consumption. However, the seasonal variation observed in HVAC system usage can be attributed to external loads, primarily heat conduction through the building envelope and solar heat gain. This observation underscores the importance of considering building envelope performance and solar shading strategies in energy optimization efforts.

In terms of modeling efficiency, BESTAI demonstrated superior performance compared with other commercially available BPS tools. The shoe-box model generation, which typically requires only a few minutes of user input, represents a significant time-saving feature. This efficiency was further exemplified in our experimental design stage, where 81 cases were simulated. The entire annual building energy simulation process for these cases was completed in just 6 h using BESTAI. This rapid simulation capability enables extensive parametric studies and optimization processes that would be time-prohibitive with conventional tools. The efficiency of BESTAI opens up new possibilities for building energy optimization. Allowing a larger number of simulations in a shorter time frame enables a more comprehensive exploration of design alternatives and energy-saving strategies. Furthermore, the suggestion that appropriate experimental design methods can further reduce the number of required simulations points to potential future enhancements in the tool's efficiency. However, note that while BESTAI's accuracy and efficiency are impressive, the tool's performance should be continuously validated across a diverse range of building types and climatic conditions. Future studies can focus on expanding the validation to include different building categories, such as residential, commercial, and industrial structures, to ensure the tool's versatility.

Step D: Experimental design

We propose to adjust the following four factors critical to this target station's energy consumption in Taiwan: air conditioning efficiency, window-to-wall ratio (*WWR*), window *U-value,* and shading coefficient (*Sc*). Every factor contains three tiers. The air conditioner can be replaced with a high energy efficiency type to increase the coefficient of performance (COP) (from 2.7 to 3.2 or 4.0, which signifies energy conservation). A reduction in window area can decrease solar radiation heat entering the interior (*WWR* from 0.9 to 0.7 or 0.5). The window *U-value* can be adjusted on the basis of whether it is double-glazed or Low-E double-glazed glass. In addition, improving the shading factor of windows with a thermal insulation film is also effective for reducing solar heat gain. Therefore, the *Sc* factor is set to 0.35, 0.55, and 0.99 owing to different visible light transmittances.

Initially, a complete factorial design was considered, which would require 81 (3^4) experimental trials. However, recognizing the time and computational constraints often present in building energy simulations, we explored more efficient experimental design methods. The Taguchi method was investigated as an alternative, offering two options: 27 (3^3) trials or nine (3^2) trials. This method provided a balance between the comprehensive coverage of the factor space and the experimental efficiency. Table 2 in our study illustrates the factor combinations using the Taguchi method.

Table 2
Taguchi method showing the experimental factors' combination.

Test No.	*AC_COP**	*WWR* (%)	*U-value*	*Sc*
1	4.0	0.9	1.64	0.55
2	2.7	0.5	1.64	0.35
3	4.0	0.5	3.31	0.86
4	4.0	0.7	5.97	0.35
5	3.2	0.9	3.31	0.35
6	2.7	0.9	5.97	0.86
7	3.2	0.5	5.97	0.55
8	3.2	0.7	1.64	0.86
9	2.7	0.7	3.31	0.55

*air conditioning system's coefficient of performance

To further optimize our experimental approach, we also utilized the JMP software to implement two additional design methods: DSD and CD. The DSD, particularly suitable for early-stage experimentation with four or more factors, allowed us to investigate quadratic model terms for continuous factors. Our DSD resulted in 12 experimental trials, as shown in Table 3 of our case study.

The CD platform in JMP offered the most flexible approach. We use the CD platform to construct optimal designs that are custom-built for the researcher's specific experimental setting. Generally, a CD is more cost-effective than a design obtained using alternative methods. If the building energy diagnostician only wants to identify the main effects affective building energy efficiency, the number of experiments generated by CD in JMP software is the same as that in the Taguchi method, as shown in Table 4. If considering the interactions of quadratic terms, JMP increases the number of experiments to 11. Note that the experiments designed by JMP directly omit the second (middle) level and use the highest and lowest levels as the configuration design, as shown in Table 5. However, such a design may overlook identifying the optimal factor combinations.

Step E: Identification of main factors of DOE testing

(1) Effects of main factors

Our study began with a comprehensive, complete factorial experimental design, conducting 81 building energy consumption simulations to identify the main factors affecting building

Table 3
Definitive screening design showing the experimental factors' combination.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*
1	2.7	0.7	5.97	0.55
2	2.7	0.9	1.64	0.35
3	2.7	0.9	3.32	0.55
4	2.7	0.5	1.64	0.86
5	3.2	0.5	5.97	0.86
6	3.2	0.5	3.32	0.35
7	3.2	0.7	5.97	0.35
8	3.2	0.9	1.64	0.55
9	4.0	0.9	5.97	0.86
10	4.0	0.5	3.32	0.55
11	4.0	0.7	1.64	0.35
12	4.0	0.7	3.32	0.86

Table 4
Custom design showing the combination of experimental factors with main effects.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*
1	3.2	0.9	5.97	0.86
2	2.7	0.5	5.97	0.35
3	4.0	0.9	1.64	0.35
4	3.2	0.5	1.64	0.55
5	3.2	0.7	3.31	0.35
6	2.7	0.7	1.64	0.86
7	2.7	0.9	3.31	0.55
8	4.0	0.5	3.31	0.86
9	4.0	0.7	5.97	0.55

Table 5
Custom design showing the combination of experimental factors with main effects and interactions.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*
1	4.0	0.9	5.97	0.35
2	2.7	0.9	5.97	0.35
3	4.0	0.5	5.97	0.35
4	2.7	0.5	5.97	0.86
5	4.0	0.5	5.97	0.86
6	4.0	0.9	1.64	0.86
7	2.7	0.9	5.97	0.86
8	4.0	0.9	1.64	0.35
9	4.0	0.5	1.64	0.86
10	2.7	0.9	1.64	0.86
11	2.7	0.5	1.64	0.35

energy consumption. The results, as illustrated in Fig. 9, revealed that the primary factors affecting building energy consumption are air conditioning efficiency, *Sc*, and *WWR*.

Air conditioning efficiency emerged as the most significant factor impacting building energy consumption in Taiwan's climate. Our analysis, based on the experimental conditions shown in Table 6, demonstrated that increasing the air conditioning system's COP from 2.7 to 4.0 can reduce the annual building energy consumption by up to 47% (Fig. 10). This substantial reduction underscores the critical role of HVAC system efficiency in building energy performance.

Window *Sc*, which is related to the amount of solar radiation entering, was identified as the second most influential factor. A higher *Sc* value allows more natural light to enter the interior, resulting in reduced indoor lighting power consumption. However, it can also lead to excessive solar radiation heat entering the interior, increasing air conditioning power consumption. Table 7 represents the experimental conditions selected from the 81 experiments conducted, with window *Sc* as the variable factor, in the full factorial experimental design. Our experiments showed that varying the *Sc* can yield energy improvement benefits ranging from 5 to 11% (Fig. 11). The experimental results from the full factorial experimental design also demonstrate that choosing air conditioning systems with different energy efficiencies does not significantly impact the energy consumption improvement benefits of installing energy-efficient glass (Sc = 0.35). However, when simultaneously using high-efficiency air conditioning systems and low *U-value* windows, there is a significant impact on the improvement in building energy consumption benefits. This finding highlights the delicate balance between natural lighting and solar heat gain in building design. Interestingly, our results also indicated significant interactions between *Sc*, air conditioning efficiency, *WWR*, and window *U-value*, suggesting a complex relationship between these factors in determining overall building energy performance.

While *WWR* was identified as a main effect factor, our analysis (Table 8) showed that its impact on building energy consumption was relatively minor compared with those of air conditioning efficiency and *Sc*. This finding suggests that, while important, adjustments to *WWR* may offer less substantial energy savings than improvements in HVAC efficiency or window shading.

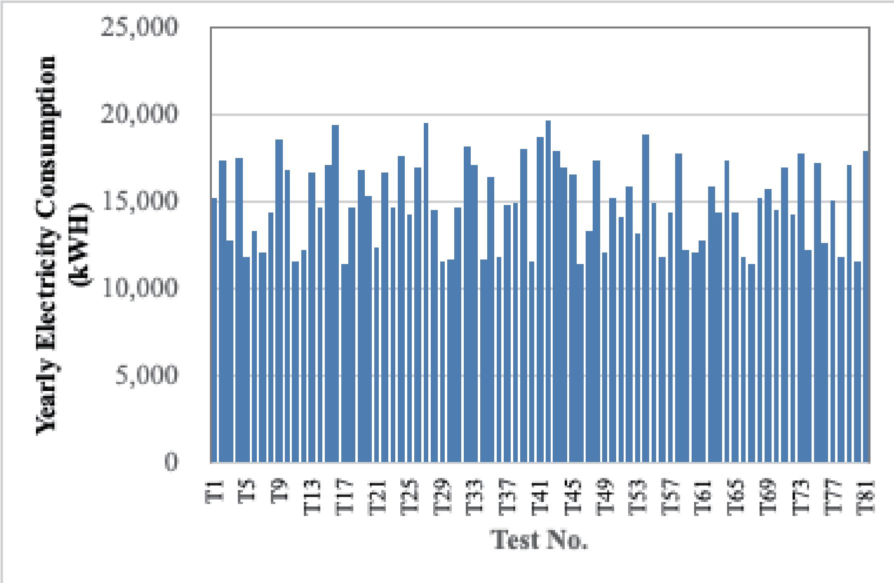

Fig. 9. (Color online) Total building energy consumption experiments by the full factorial experimental design.

Table 6
Trial tests with *AC_COP* as the main effect factor.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*
17	4.0	0.5	1.64	0.35
19	2.7	0.5	1.64	0.35
30	4.0	0.5	5.97	0.35
33	2.7	0.5	5.97	0.35
43	2.7	0.5	5.97	0.86
74	4.0	0.5	5.97	0.86

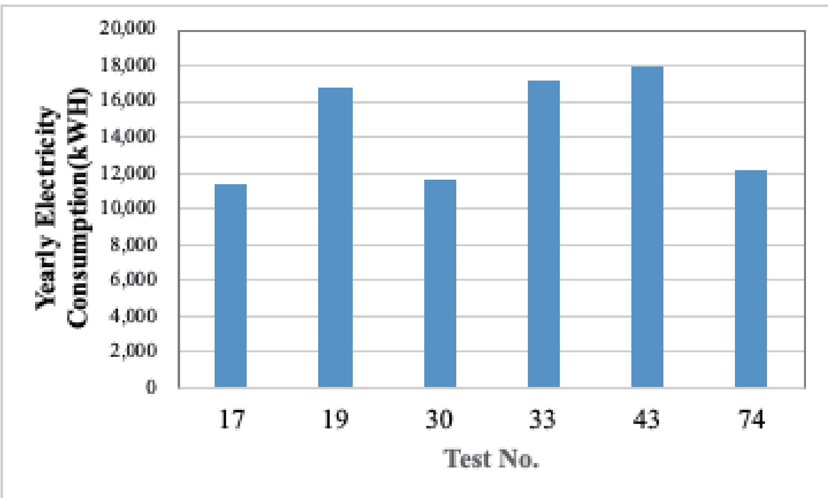

Fig. 10. (Color online) Comparing the energy consumption of trial tests with *AC_COP* as the main effect factor.

Table 7
Trial tests with *Sc* as the main effect factor.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*
30	4.0	0.5	5.97	0.35
74	4.0	0.5	5.97	0.86
56	4.0	0.7	1.64	0.55
80	4.0	0.7	1.64	0.35
33	2.7	0.5	5.97	0.35
43	2.7	0.5	5.97	0.86
61	4.0	0.7	1.64	0.86
80	4.0	0.7	1.64	0.35

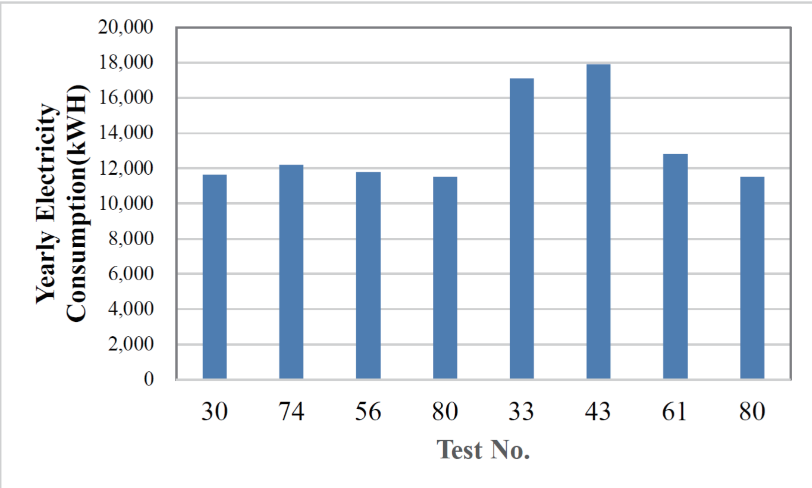

Fig. 11. (Color online) Comparing the energy consumption of trial tests with *Sc* as the main effect factor.

Table 8
Comparing the energy consumption of trial tests with *WWR* as the main effect factor.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*	Annual electricity consumption (kWH)
11	4.0	0.9	3.31	0.35	11597
46	4.0	0.5	3.31	0.35	11404
13	2.7	0.5	3.31	0.35	16763
15	2.7	0.9	3.31	0.35	17048

(2) Interaction effects

In JMP software, through a full factorial experimental design, the two-way interaction factors between the four factors obtained are the main factors for improving building energy consumption, which are air conditioning system's coefficient of performance (*AC_COP*)**Sc*, *U-value***Sc*, and *WWR***Sc*.

Table 9 shows the two-way interaction factor (*AC_COP***Sc*) between air conditioning efficiency and window *Sc* on changes in building energy efficiency, and using the highest efficiency air conditioning and low-*Sc* (high solar insulation) windows results in a 54% reduction

Table 9
Trial tests that include the interaction factor between *AC_COP* and *Sc*.

Test No.	*AC_COP*	*WWR* (%)	*U-value*	*Sc*	Annual electricity consumption (kWH)
5	4.0	0.5	5.97	0.55	11776
33	2.7	0.5	5.97	0.35	17109
30	4.0	0.5	5.97	0.35	11636
43	2.7	0.5	5.97	0.86	17929

in building electricity consumption (T30) compared with using the lowest efficiency air conditioning and high-*Sc* (poor solar insulation) windows (T43). The results of the full factorial experimental design for energy efficiency improvement in existing buildings emphasize the potential for synergistic effects in energy-saving strategies, particularly when air conditioning efficiency and window *Sc* can maximize energy savings in existing buildings.

(3) Comparison of experimental design methods

In this study, we compared four experimental design methods: full factorial, Taguchi, DSD, and CD. The results, summarized in Table 10, revealed both consistencies and differences across methods.

All methods identified air conditioning efficiency and window *Sc* as the main effect factors, confirming their critical role in building energy performance. The full factorial and DSD methods also identified *WWR* as a main effect factor, while in the case of Taguchi experimental design, we found that the main effect factors for improving energy efficiency in existing health-caring buildings are air conditioning efficiency and window *Sc*. The CD method considered all four variables (including *U-value*) as the main effect factors, potentially overestimating the importance of some factors.

Significant differences were observed in the identification of two-way interaction factors across methods, with CD identifying the most interactions and Taguchi the least. Taguchi's experimental design only considers the interaction between air conditioning efficiency and window *Sc*. In contrast, the DSD method includes the interactions between window *U-value*, which was not included as a main effect factor, and the third main effect factor, *WWR*, as part of the two-way interaction factors. As for the CD method in JMP software, it selects five two-way interaction factors. These differences highlight the importance of method selection in experimental design, as it can significantly impact the identification of key factors and their interactions.

(4) Implications for building energy efficiency in Taiwan

Over the past decade, the Taiwanese government has consistently encouraged the replacement of incandescent bulbs and inefficient appliances with LED light bulbs and high-efficiency home appliances through subsidy policies. This policy has led to an approximate 90% market share for LED light bulbs and the widespread adoption of high-efficiency air conditioning systems. Our findings align with and support Taiwan's recent policy initiatives promoting the adoption of LED lighting and high-efficiency appliances. The identification of air conditioning efficiency as the primary factor for improving building energy efficiency validates these policy directions.

Table 10
Main effect and interaction factors from four different DOE methods.

DOE	Main effect factor				Interaction factor
	AC_COP	*Sc*	*WWR* (%)	*U-value*	
Full factorial	V	V	V	X	*AC_COP**Sc*, *U-value**Sc, *WWR**Sc*
Taguchi	V	V	X	X	*AC_COP**Sc*
DSD	V	V	V	X	*U-value**WWR*
CD	V	V	V	X	*AC_COP**Sc*, *U-value**Sc*, *WWR**Sc*, *AC_COP**U-value*, *AC_COP**WWR*

Looking forward, our results suggest that focusing on reducing window *Sc* and optimizing *WWR* can be the most effective strategies for further improving energy efficiency in existing buildings. These approaches offer a balance between energy efficiency improvements, cost-effectiveness, and ease of implementation, making them particularly suitable for retrofitting existing structures.

Step F: Optimizing energy efficiency solutions

Analysis of variance (ANOVA) is typically used to identify main effect factors, with decisions about factor significance based on *P*-values. However, for building diagnosticians who may lack extensive statistical training, the Prediction Profiler feature in JMP software proves to be an invaluable tool. It allows for the quick visualization and understanding of individual factors and interaction effects on building energy efficiency. This aligns with one of the primary objectives of conducting DOE through JMP software, that is, to uncover optimal solutions for enhancing energy efficiency in existing structures.

Our analysis, as illustrated in Fig. 12, reveals that the optimum yearly electricity consumption was approximately 11,384 kWh. This optimal result was achieved with a combination of factors: *AC_COP* at 4, *Sc* at 0.35, *WWR* at 0.5, and *U-value* at 1.64. The 95% confidence interval for yearly electricity consumption ranged from 10,866 to 11,901 kWh, providing a robust estimate of the potential energy savings.

The Prediction Profiler graphs offer valuable insights into the desirability of the regressive model. A notable observation is that increasing *AC_COP* from 2.7 to 4.0 resulted in a substantial increase in desirability from 0 to 0.76. In contrast, adjusting the *WWR* had minimal impact on desirability. This visual representation clearly indicates that enhancing the efficiency of the air conditioning system is the most significant approach to improving energy efficiency in existing buildings. Furthermore, the Prediction Profiler tool demonstrates that yearly electricity consumption reaches its optimum level when *AC_COP* is at its highest level, while *Sc*, *WWR*, and *U-value* are at their lowest levels. Specifically, to achieve optimal energy efficiency, the COP of the air conditioner should be 4.0, *WWR* should be 0.5, *Sc* should be 0.35, and the thermal transmission of windows should be 1.64 W/m^2-K.

Following the estimation of main effect factors and the visual evaluation of relationships between response variables and predictors, we fitted regression models to the data generated by BESTAI using various DOE methods. Table 11 presents these regression models, considering regression coefficients and effects. The models derived from full factorial, Taguchi, DSD, and

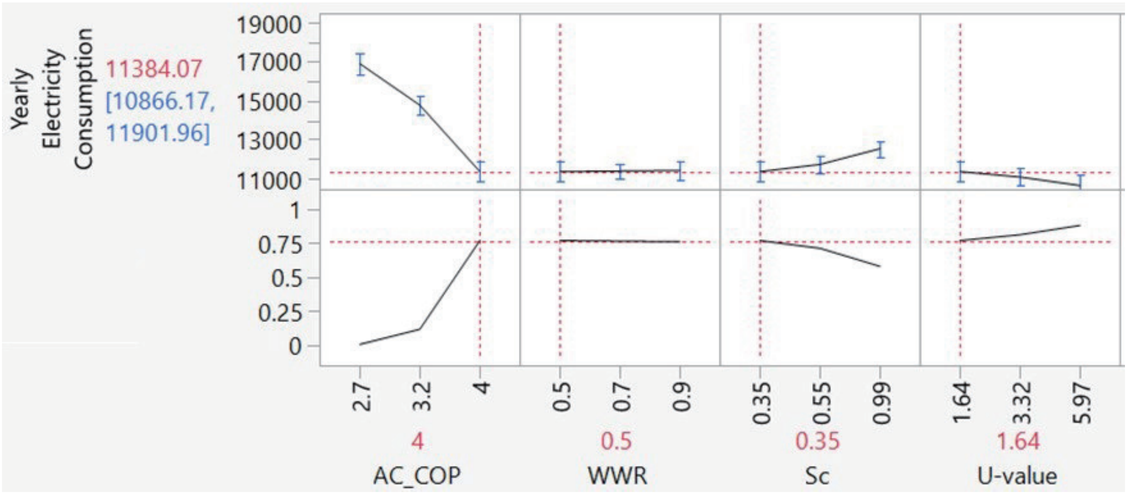

Fig. 12. (Color online) DSD model optimization using profiler tool in JMP software.

Table 11
Predicted regression models by various DOE methods.

DOE	Regression model
Full factorial	14632.76 − 2812.86*((*AC_COP* − 3.35)/0.65) + 584.19*((*WWR* − 0.6)/0.3) + 568.41*((*Sc* − 0.67)/0.32) + ((*AC_COP* − 3.35)/0.65)*(((*Sc* − 0.67)/0.32)*(−132.884)) + ((*WWR* − 0.6)/0.3)*(((*Sc* − 0.67)/0.32)*389.74) + ((*U-value* − 3.81)/2.17)*(((*Sc* − 0.67)/0.32)*(−154.15))
Taguchi	14822.39 − 2923.34*((*AC_COP* − 3.35)/0.65) + 718.90((*Sc* − 0.67)/0.32) + ((*AC_COP* − 3.35)/0.65)*((*Sc* − 0.67)/0.32)*(−550.03)
DSD	14765.12 − 2765.54*((*AC_COP* − 3.35)/0.65) + 386.98*((*WWR* − 0.7)/0.2) + 587.23*((*Sc* − 0.67)/0.32) + ((*WWR* − 0.7)/0.2)*(((*U-value* − 3.81)/2.17)*358.70)
CD	15076.71 − 2888.76*((*AC_COP* − 3.35)/0.65) + 712.74*((*Sc* − 0.67)/0.32) + 423.33*((*WWR* − 0.7)/0.2) + 15.33*((*U-value* − 3.805)/2.165) + ((*AC_COP* − 3.35)/0.65)*(((*Sc* − 0.67)/0.32)*(−113.24)) + ((*AC_COP* − 3.35)/0.65)*((*WWR* − 0.7)/0.2*(−77.58)) + ((*AC_COP* − 3.35)/0.65)*(((*U-value* − 3.81)/2.17)*59.43) + 211.93*((*Sc* − 0.67)/0.32)*((*WWR* − 0.7)/0.2) − 106.08*((*Sc* − 0.67)/0.32)*((*U-value* − 3.81)/2.17)

CD methods each offer unique insights into the relationships between factors and energy consumption.

To validate the accuracy of these models, we compared their predictions with the results obtained from BESTAI simulation under optimal energy-saving conditions (Table 12). The DSD experimental design method demonstrated the highest accuracy, with a remarkably low prediction error of approximately −0.15%. This was closely followed by the Taguchi experimental design method, with a prediction error of 1.22%.

Interestingly, despite using 81 experiments, the full factorial method's predicted values also fell within a reasonable range, with an error of −2.07%. The CD experimental design method, while including main effect and interaction factors, paradoxically showed the highest prediction error at −6.35%. This unexpected result underscores the complexity of energy efficiency modeling and the importance of selecting appropriate experimental design methods.

These findings have significant implications for both researchers and practitioners in the field of building energy efficiency. The superior performance of the DSD method suggests that it may be a more efficient approach for optimizing building energy consumption, potentially

Table 12
Optimal annual electricity consumption by various DOE methods.

	AC_COP	*Sc*	*WWR*	*U-value*	Predicted annual electricity consumption (kWH)	Error (%)
BESTAI					11401	—
Full factorial					11165	−2.07
Taguchi	4.0	0.35	0.5	1.64	11540	1.22
DSD					11384	−0.15
CD					10677	−6.35

reducing the number of required simulations without compromising accuracy. The Taguchi method's strong performance also indicates its viability as a robust tool for energy efficiency optimization.

The regression models derived from these DOE methods provide valuable insights into the relative importance of different factors in determining building energy consumption. Across all models, the *AC_COP* consistently emerged as the most influential factor. This underscores the critical role of HVAC system efficiency in overall building energy performance and suggests that upgrading or optimizing air conditioning systems should be a priority in energy retrofit projects.

The interaction effects identified in these models, particularly between *AC_COP* and *Sc*, as well as between *WWR* and *U-value*, highlight the complex interplay between building envelope characteristics and HVAC system performance. These interactions emphasize the need for a holistic approach to building energy optimization, considering both active and passive energy-saving strategies.

In conclusion, our study demonstrates the efficacy of various DOE methods in optimizing building energy efficiency. The DSD method, in particular, shows promise as a powerful tool for accurately predicting and optimizing energy consumption with minimal experimental runs. The consistency in identifying *AC_COP* as a critical factor across all models underscores the importance of focusing on HVAC system efficiency in energy retrofit strategies.

4. Discussion

In this study, we present a unique framework that integrates the BESTAI simulation tool with statistical experimental design methodologies to enhance energy efficiency in long-term care (LTC) facilities. While previous research has focused on optimizing energy consumption in residential and commercial buildings, limited studies have specifically addressed LTC centers, which have unique operational characteristics and occupancy patterns. By targeting Taiwan's Tier C LTC centers, we provide a practical and scalable approach to achieving the nation's 2050 net-zero emissions goal. The combination of high-accuracy BPS and efficient experimental design techniques distinguishes this work from existing studies. Several prior studies have explored energy efficiency in healthcare and residential buildings using BPS and optimization techniques. For example, Peng *et al.*(22) applied a genetic algorithm to optimize energy efficiency in hospitals, demonstrating significant energy savings but requiring extensive computational resources. Similarly, Vergés *et al.*(23) utilized an artificial neural network to predict HVAC energy consumption, but the models' accuracy is challenging, and the inability to analyze variable refrigerant volume in nursing homes increased the tendency to overestimate cooling consumption. Unlike these studies, our research employs the BESTAI tool, which is user-friendly and accessible, making it suitable for practitioners without advanced simulation expertise. Furthermore, our comparative evaluation of full factorial, Taguchi, DSD, and CD approaches contributes to methodological advancements in energy efficiency research. While full factorial designs are comprehensive, they are often computationally expensive, as shown in a previous study.(24) In contrast, we demonstrate in this study that Taguchi and DSD methods provide equally reliable results with significantly fewer trials, offering a more practical and cost-effective solution for LTC facility managers.

5. Contributions and Policy Implications

The findings of this study have direct implications for policymakers and facility managers. The identification of air conditioning efficiency and window *Sc* as the most influential factors aligns with previous research on passive and active energy-saving strategies.(25) However, our research provides a more targeted analysis for LTC centers, emphasizing rapid implementation and cost-effectiveness. By achieving a 47% reduction in electricity consumption through optimized configurations, we underscore the potential for substantial energy savings without extensive structural modifications. Moreover, the proposed methodology can be replicated and adapted to different regions, contributing to global sustainable development efforts. Future research can explore additional factors, such as renewable energy integration and occupant behavior modeling, to further enhance energy efficiency in LTC facilities.

6. Conclusions

In this paper, we presented a novel framework for enhancing energy efficiency in existing long-term care centers in Taiwan, addressing the dual challenges of climate change mitigation and an aging population. Our integrated approach, combining the BESTAI simulation tool with JMP software for experimental design, offers a robust methodology for optimizing building energy performance. The integration of BESTAI and advanced experimental design methods enables the precise analysis and optimization of energy usage, similar to how microactuators and energy harvesters enhance energy management in various applications. By improving air conditioning efficiency, window insulation, and shading strategies, our study contributes to reducing overall energy demand, aligning with the broader goal of sustainable energy utilization. Key findings of this research include the following:

(1) The BESTAI tool demonstrated high accuracy in simulating building energy consumption, with less than 3% deviation from metered results, validating its reliability for energy audits and retrofitting strategies.

(2) Among the four factors investigated (air conditioning efficiency, *WWR*, window *U-value*, and *Sc*), air conditioning efficiency emerged as the most significant factor affecting building energy consumption, followed by window *Sc*.

(3) The DSD and Taguchi methods proved to be the most cost-effective experimental design approaches, requiring only 11 and 9 trials, respectively, to achieve optimal energy-saving solutions, compared with the full factorial design's 81 trials.
(4) The regression models derived from these methods consistently identified the air conditioning system's COP as the most influential factor, underscoring the critical role of HVAC system efficiency in overall building energy performance.
(5) Interaction effects, particularly between COP and Sc, as well as between *WWR* and *U-value*, highlight the complex interplay of building envelope characteristics and HVAC performance, necessitating a holistic approach to energy optimization.

These findings have significant implications for policymakers and building managers in Taiwan's long-term care sector. They provide a scientific basis for prioritizing energy efficiency measures, focusing on upgrading HVAC systems and improving window shading as primary strategies for reducing energy consumption.

The framework developed in this study, integrating user-friendly simulation tools with statistical analysis, offers a replicable model for energy efficiency optimization in other building types and geographical contexts. It addresses the need for rapid, accurate, and accessible methods for building energy analysis, crucial for meeting Taiwan's ambitious net-zero emissions targets by 2050. Future research can significantly enhance this study's energy optimization framework by incorporating sensor technology. Smart sensors can provide the real-time validation of the BESTAI simulation results while enabling the granular monitoring of the identified critical factors. Occupancy sensors can further refine the energy consumption models by capturing the actual usage patterns in different zones of the long-term care facility, enabling more precise HVAC control strategies. The integration of IoT-enabled power meters can provide equipment-level energy consumption data, allowing facility managers to verify the reduction in electricity usage predicted by simulation. Additionally, thermal imaging sensors can monitor the building envelope's performance. This sensor-enhanced approach will create a feedback loop between simulation predictions and actual performance metrics, enabling the continuous optimization of the energy-saving strategies identified in this research.

Acknowledgments

The authors wish to express their sincere appreciation to the Architecture and Building Research Institute, Ministry of Interior, Taiwan (project number: 11363B0007) for the financial support so that this project could be carried out smoothly.

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