

Energy Performance Modelling and Consumption Forecasting in Built Environments

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Abstract: For all sector of the economy including the construction sector, energy consumption forecasting is critical for future planning. The building sector accounts for a staggering 30% of the world's energy use and one-third of associated greenhouse gas (GHG) emissions worldwide. Modeling of building energy performance and consumption forecasting is significant for energy policy formulation, fixing targets and control energy usage to provide a long term energy security. Many energy models are accessible now, but the area is still under development and needs perfection on several counts. To select the most suitable and appropriate model for a specific purpose, it is often hard to evaluate the various models and their characteristics. This article provides a broad analysis of modeling methods, classification, and applications in constructed settings with an improved focus. A critical assessment of various models is also provided based on their composition, input-output relationships, strengths, and weaknesses to define study gaps and provide directions for future studies.

Keywords: Artificial neural network, Bottom-up, Energy consumption, Energy forecasting, Energy performance modeling, Machine learning Top-down etc.

I. INTRODUCTION

The building sector is growing very rapidly and globally accounts for about 30 % of total energy consumption and one-third of related green house gas (GHG) emissions [1]. Building rates are so fast in a few Asian and African nations that the world will add nearly 230 billion square meters of floor area to the planet every week in the form of new buildings over the next 40 years [1]. This will further boost the energy demand for different purposes such as lighting and space conditioning. Coupled with many other issues such as energy security and environmental concerns, increasing demand has led to significant attempts to decrease energy consumption and improve efficiency effectiveness. Opportunities for energy consumption reduction are enormous. In the building sector alone, it can be reduced by 20% through retrofits, policy formulation, and increased deployment of smart technologies [2]. According to the directive 2010/31 of the European Union (EU), the priority objective for all new buildings by December 2020 is to be nearly "zero-energy buildings" [3]. Yet many buildings constructed decades ago are still energy-inefficient and have no breakthrough. The energy savings potential largely remains untapped due to lack of effective regulations, policies, and continued use of inefficient technologies. Energy modeling in buildings is a computer-based simulation process to quantify energy consumption as a function of the

building envelop, operational, behavioral, and external parameters. Modeling of energy performance and quantification of energy consumption in buildings can lead to several efficiency improvement measures such as retrofits, technology adoption, or even re-construction of inefficient environments. The building sector is a complex system and several parameters affect its performance. Hence precise consumption prediction is rather difficult. Weather is undeniably a complex process and cannot be accurately predicted beyond a week to ten days. The other reasons are the identification of relevant parameters, their precise measurement, initial conditions of the selected parameters, and their stochastic behavior. However, the models are being used for several purposes, such as upgradation, adoption of new technology, change in energy consumption of a particular dowering due to retrofits, design of new buildings, and determination of macro-scale energy supply requirements [4]. A variety of models are found in academic databases [5-8] but, energy modeling still presents a challenge and has a significant performance gap between the simulation and the true results. It is often difficult to assess the numerous models and their features to decide the most suitable model for a particular purpose. A classification scheme can provide some insight into model features and differences and similarities among them. User's behavior is critical for the energy consumption and performance of the buildings. Current practices do not display the necessary elegance to reflect end-users behavior, control actions at their level, and the interactions between indoor and outdoor weather conditions. Nowadays, models based on artificial intelligence such as neural network and support vector machines are extensively used because of their high performance, accurate nonlinear mappings, and their capability to incorporate the effect of parameters which cannot be assessed accurately [9-10]. These methods are based on Machine Learning (ML) and their developments. However, all models are not suitable and applicable for all type of cases, so it is necessary and meaningful to analyze them to ensure their effectiveness and applicability [11]. This article provides a broad analysis of modeling approaches, classification, and applicability in built environments with a focus on improving energy performance measures. A critical assessment of different models based on their structure, input-output relations, strengths, and weaknesses is also presented to identify the research gaps and provide directions for future research. Section 2 defines the energy performance modeling process and the connected issues in the built environment; section 3 gives a comprehensive overview of modeling approaches, challenges, and classification; section

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5 discusses various models to demonstrate their structure, strengths, weaknesses and applications. Finally section 6 outlines the conclusions drawn from the study.

II. ENERGY PERFORMANCE MODELING FOR BUILT ENVIRONMENT

Energy Performance Modeling (EPM) is a computer-based process to quantitatively predict the building response to key changes in structural, operational, behavioral and external variables. The models usually comprise of variables and interactions between them. They can be built on fundamental physical principles and sound engineering practices, statistical or machine learning techniques or a combination of these and are classified accordingly. The response/output may include primary energy consumption, carbon dioxide emissions, energy, and operational costs, or energy efficiency of the system under investigation. Energy demand and load forecasting, indoor environmental quality, equipment performance, building automation and operational control optimization are the other significant aspects of EPM [12]. The structural inputs that are needed and affect the building performance are building geometry, construction materials, appliances, and their operation schedule, occupants and their behavior. The complex nature of buildings and a large number of factors affecting their performance make the process of energy performance modeling difficult as compared to other sectors of the economy.

The discrepancy between simulation results and the actual performance stems from selection and approximations of input variables such as prevailing weather conditions, properties of the materials used and the user's behavior. The interrelation between buildings and the environment is an important challenge. Gradual climate change, extreme weather events can impact both energy consumption and occupant's behavior. Many people spend their considerable time at home, and the quality of the indoor environment has a significant effect on their lives. The main function of buildings is to provide comfortable living conditions. However, all buildings do not meet this challenge and have several performance issues. Reducing energy consumption, improving efficiency, and indoor environment are the key initiatives for the designers and building owners world over. A variety of modeling techniques, ranging from broadly economic to engineering are employed [4, 6, 7]. The ease of inputs and accessibility of output data varies widely between the models and tools employed.

The building parameters are so complex and large in number that deterministic relationship between the causative factors and energy performance is rather difficult. To develop a reliable predictive model, it is necessary to take into account the key variables. But such a choice of variables is the pervasive issue in the buildings energy performance modeling while endeavoring to keep the demonstrate basic. Most of the energy models focus on the quantitative analysis of the buildings while understanding and managing the role of end-users, quality of indoor air, and long term load forecasting remains a challenge. Tools and methods for assessing the behavior of consumers and their preferences are moderately covered in the literature. Accuracy of forecasts

also depends upon the time horizon. For example, it is possible to predict the next day load within reasonable accuracy but, it is not possible to predict the next years' peak load accurately as it involves long-term weather forecasts which are not available.

III. APPROACHES FOR ENERGY PERFORMANCE IN BUILDINGS

Broadly, there are two fundamental approaches: top-down and bottom-up. Both the approaches are used for medium to long-term forecasting. The difference between the two is related to the sectorial use, technology aggregation and the manners in which adoption of technologies is treated. A critical analysis has been provided by Ugursal et al. [4] and C. Koulamas et al. [13]. This section attempts to categorize the key approaches and their usage in the building life cycle.

1. Top-Down Approach

TOP-down modeling, in a global context, is an econometric approach that starts from aggregated level and examines the relationship between total energy consumption in different sectors (building, transport, agriculture, and industry) and the economy at large [14]. It is used for demand/ supply analysis, scenario analysis, future predictions, and to assess the long term impact of policies and other economic variables. The aggregated data is utilized for energy consumption projections using macroeconomic indices such as GDP, employment rates and price elasticities. Similarly, in the building sector, the top-down approach uses the total energy consumption of the whole building stock and regresses it as a function of variables such as the number of units, building features and climatic parameters [15]. The method tries the best fit to predict the results assuming that the future will follow the trend. The aggregated forecast is then associated with individual units and the end-use items (lighting, water heating, space heating, and air conditioning) based on their historical relative frequency. The approach is quick and saves on both the material and labor costs. Saha and Stephenson [16] developed an econometric model to simulate residential energy use for four end uses employing technological, economic and demographic determinants. The model demonstrates that with proper technology use, the zero-energy growth is quite possible with little or no effect on lifestyle. To determine changes in energy utilization patterns or trends on a long-term basis, the top-down approach seeks factors such as income or broad characteristics of the entire housing stock. Accordingly, the models can be categorized as econometric or technological. For example, the economic model can be used to determine the effect of a given energy price movement on energy demand or energy-related carbon emissions, whereas, the technological models attribute the energy utilization to characteristics of the entire building stock [4]. A prior condition for the utilization of top-down models is the continuity in energy use patterns and underlying variables for the projection period [17]. However, the data obtained from the household appliances such as lights, washing machines, vehicle charging, etc. is rather variable as compared to premise level

aggregated data. Many devices often record zero consumption as we do not operate them continuously. Forecasting inaccuracy does stem in if the approach fails to account for such variability in the data. Home appliance stocks and consumption patterns are dynamic in nature and change with time. As such, the top-down approach may not be able to provide a good fit, particularly over short periods. In such cases, forecasting using bottom-up may be a good answer as it provides a better understanding of appliance behavior and accounts for an ever-changing landscape of energy consumption, peak demand, and consumer behavior.

2. Bottom-Up Approach

Opposite to top-down modeling, bottom-up modeling is a sectorial approach that focuses on end-use household subsystems and scenario development. It is a medium-term physical approach and uses disaggregated inputs to construct predictive scenarios. The promising options can be combined to design a bigger representative scenario or model that can be extrapolated to higher level (regional or national) to address issues concerning the reduction of energy consumption, efficiency or to answer questions: how can a given emission reduction task be achieved at a minimum cost at the household or higher level? The end-use approach requires detailed information about the building, equipment, and the customers and their behavior. However, a collection of detailed energy consumption data over short intervals is a major constraint and time-consuming aspect of bottom-up approaches. Lack of granularity is yet another important aspect of residential data sets. Therefore, most of the studies center on modeling energy utilization in buildings on monthly rather than hourly or daily basis. The data for such studies is usually collected from energy bills and utility statements.

Deployment of smart technologies (smart meters, sensors, Wi-Fi etc.) in buildings is, however, helping to overcome this problem [2]. For example, sensors and smart meters can be used to collect online energy consumption information from each household appliance and transfer the same to the data center using Wi-Fi communication, thus contributing to the accuracy of forecasting. Sensors are more reliable in measuring data over short intervals and provide the actual state of the building for energy consumption prediction. This approach has been exploited within the system of the Green@Hospital project where the outdoor and indoor temperatures were predicted 8 hours ahead to control hospitals' HVAC units optimally leading to a significant energy consumption reduction and overall energy efficiency improvement [18].

IV. CLASSIFICATION OF APPROACHES FOR BUILDING ENERGY PERFORMANCE MODELING

Over the years, categorization of models for energy performance in built environments has been dealt with by numerous researchers. The categorization provided is soft and mixed-paradigm models have been detailed. Pendeson [19] classify the models into statistical/ regression analyses, energy simulation programs, and intelligent computer systems; Swan and Ugursal [4] proposed two primary bunches for the models -top-down and bottom-up, whereas, Zhao and Magoulès [20] categorized them into five groups:

engineering, statistical, neural networks, machine learning, support vector machines, and hybrid. Be that as it may, the three approaches - neural networks, support vector machines, and machine learning - can be collectively alluded to as artificial intelligence or ML -based approaches. Nelson Fouquier et al. [21] categorizes the approaches into three groups: engineering, statistical, and hybrid and Seyedzadeh et al. [22] categorize them into four groups: engineering calculation, statistical modelings, machine learning, and simulation model-based benchmarking. A condensed comparison of the models has been given by Fatima et al. [23] and K. Arendt et al. [24]. Figure 1 appears the tree chart of building energy modeling approaches.

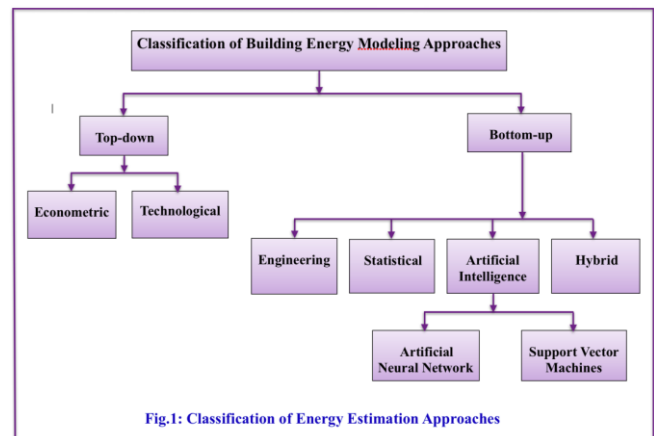


Fig.1: Classification of Energy Estimation Approaches

V. ENERGY MODELS FOR BUILDING ENERGY PERFORMANCE AND CONSUMPTION FORECASTING

A. Engineering Models

Engineering modeling is a flexible method based on physical principles and thermodynamic mass balance equations. These models are too known as physical or white-box models. Engineering modeling requires complex mathematics, engineering domain knowledge, and a detailed portrayal of the building wrap, equipment, and appliances installed, internal and external heat gain and local climatic factors to portray the heat balance and, if the same is available, the approach offers a better choice. Several simulation programs are available to unravel the equations rooted in thermodynamics and calculate the building loads. Typical simulation programs include EnergyPlus, eQuest, and Ecotect. EnergyPlus is a console-based whole-building energy simulation program based on the foremost prevalent highlights and capabilities of BLAST and DOE-2.1E. It reads input and composes yield to text files using a simple spreadsheet-like interface and provides a good insight into the building operations [27]. The program assesses heating and cooling loads of a typical dwelling unit by multiplying the building component areas with the corresponding U-values and the effective

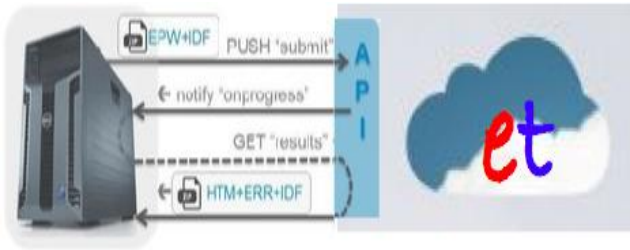


Fig. 2: Conversion of Fortran Code to C++ Computing Environment for EnergyPlus

temperature distinction (fabric losses). In the case of the cooling stack, the warm pickups from internal and external sources and the air exchange rate are also considered. Crawley et al. [28] give an itty-gritty outline of major building physical models counting their highlights and capabilities. In addition to whole winging performance analysis, engineering models, also find their applications in retrofit design, HVAC sizing, energy-efficiency code development & compliance, asset ratings, and policy assessment. Lam and Hui [29] conducted a sensitivity assessment of office structures to evaluate the effect of input parameters on annual energy usage and peak loads utilizing DOE-2. The findings indicate that buildings' heat efficiency is highly susceptible to internal loads and window structures. In the built environment, energy consumption has a powerful correlation with external weather conditions. Research by Istiaque et al. [30] in Dhaka city, shows that an air temperature of 1°C can save 81 MV of electricity consumption. Papa et al. [31] addressed the impact of weather parameters and found that in engineering models air temperature and solar radiation together can be used as a single input to represent the weather conditions. Griffith and Crawley [32] suggested a methodology using EnergyPlus to assess US business buildings' energy efficiency and technical potential of zero-energy buildings. Manandhar et al. [33] used EnergyPlus to model HVAC loads for residential and commercial buildings having distinct operation schedule and found that significant energy savings can be achieved by altering temperature and operation schedule. Although EnergyPlus universally find its applications, it still suffers from several drawbacks. The big amount of inputs needed to characterize the configuration of building and selection of U-values of the different components make the modeling difficult, time-consuming, and expensive [34]. Detailed information is rarely accessible to define the dynamic properties of building's parts, machinery or material used correctly. Modelers use ASHRAE Handbook of Fundamentals or label information from the manufacturer in most cases to estimate the U-values. Autodesk has recently produced interesting adjustments to the EnergyPlus tool kit. It is investing heavily in tackling its limitations and enhancing its codebase to extend its capabilities. EnergyPlus 8.0 Fortran code has since been transformed into a contemporary C++ computing environment (Figure 2) to overcome the performance issues and operate it quicker than a desktop on the cloud.

B. Statistical Models

The statistical or black-box models use measured data to develop a functional relationship (model or equation) between building energy consumption and the input variables [35]. Since statistical models use measured data to calibrate

the model, they are also classified as data-driven models and are widely used because of their simplicity. Unlike engineering models, statistical models require fewer variables and much less domain knowledge. If the building is too complex to describe but can be observed or measured, statistical models are the most convenient to apply. The model structure may be linear or non-linear and depends on the input and output relationship. Linear regression is a simple technique involving only two predictor variables and provides a baseline estimate. Multivariate regression modeling, however, use multiple variables such as solar radiation, wind speed, the outdoor temperature to predict a single output (energy consumption). If more than three variables are considered, the statistical modeling may not be a viable option. A detailed review of the statistical modeling techniques can be found in [36]. Linear regression analysis can be performed using Microsoft Excel or statistical package such as IBM SPSS® Statistics, STATGRAPHICS, SAS or SIMCA that greatly simplify the use of linear regression equations. Simple linear regression analysis based on a longer period offers better estimate irrespective of the type of model chosen. The case study [36] which apply linear regression analysis to predict energy utilization in a building and show that the models' performance improves with the expand of the time interval of data observation because the discrepancies due to person effects are averaged over longer periods. To understand the effect of energy management on energy consumption in smart homes using linear regression analysis, Milesane et al [37] predicted the energy consumption from the computed regression equation. The results indicate a significant reduction in energy consumption due to better heating and cooling control and energy management. Most of the statistical models focus on medium-term (monthly) energy predictions because building data generally lack granularity. The data for such predictions is usually collected from monthly utility statements. Weather variables are major influencing factors for energy consumption in built architecture. The functional relationship between load and weather variables is not stationary and depends on Spatio-temporal conditions. Conventional regression techniques produce average results because they lack the necessary versatility to address such variations.

C. Artificial Intelligence-based Models

Machine learning is a process which provides a system the capacity to learn by its own from data that we provide without being programmed [38-39]. It is an application of AI, aimed at developing suitable computer programs that can take better decisions without human intervention by simply looking at patterns in the data. Buildings energy performance modeling using ML involves creating a model by integrating input and output of the program that functions as a block box and need no information about the building system. The model receives past data, representing the behavior of the building for which the results are known, as input and use statistical analysis to predict the outcome.

The prediction process is usually divided into two distinct learning and training phases. The learning phase consists of training the

machine with past datasets. However, to achieve better results, the models need to be trained on large datasets so to handle more cases. During the prediction phase, a new data set is used for which the results are not known. Simplicity, speed of calculation and capacity to learn from examples are some of the noted advantages of these models. Several AI-based models have been developed in the past; the well-known include Artificial Neural Network (ANN) and Support Vector Machines (SVM) [40].

C1. Artificial Neural Network

ANN is a flexible brain-inspired system capable of identifying the relationship (linear or non-linear) between the inputs and the outputs [41]. The networks are now widely used to approximate a non-linear function or to tackle ill-defined problems which are too complex for humans to extract any meaningful result. The process of modeling involves creating a flexible network that changes its structure based on the inputs and training it with existing datasets. The structure of a typical neural network consists of several computational units (nodes) organized into different layers to form a network. In a layer, each node is connected to all the nodes of the succeeding layer and has one or more weighted input connections and a transfer/ activation function. Each node aggregates the results of input multiplication with the associated weights and transform it as input to the output layer. The training phase comprises selecting the network structure (number of hidden layers, nodes per layer, transfer functions) and the inputs that provide the best result. The structure is iteratively altered several times to produce the best results. To avoid over-fitting, the data set is generally divided into three data sets – training, validation, and testing. After training, the network is fine-tuned using the validation data set and finally checked for accuracy and effectiveness as a model using the test dataset. Whenever the outcome doesn't match the expected outcome, the back propagation technique [42] can be used to adjust the hidden layers of the network. Deep learning neural networks is another important advancement, where different layers of a network extract different data features until the output does not match the expected results.

The neural networks possess great learning abilities and their applications range from car automation, fraud detection, reading the human mind, learning handwriting, language recognition to predicting the energy performance of buildings. Park et al. [43] developed an algorithm to forecast electric load in buildings using current and future temperatures. The average errors observed in 1-hour and 24-hour ahead forecasts are 1.40% and 2.06% respectively which compares well with average results. Kalogirou [44] demonstrated the capability of ANNs as an effective approach for building energy performance and prediction modeling. Neto et al. [45] compared the predicted energy utilization of university buildings of São Paulo using EnergyPlus and ANN. Weather variables were used as inputs to investigate the impact. The findings address the effectiveness of ANN models and concluded that external temperature as a single input is sufficient to represent the weather conditions. The study further points out that uncertainty in results are mainly due to the improper assessment of occupancy and lighting.

Hong et al. [46] carried out multivariate analyses of several UK school buildings to assess the impact of building characteristics on energy utilization [46]. Building energy performance is also significantly affected by the accuracy in Building Information Modelling representation (BIM) - a process for handling development ventures on a digital platform. Ahmed [47] developed a model to reduce the difference between predicted and actual results by integrating BIM with the ANN which indicated significant improvements.

C2 Support Vector Machines

Support vector machine (SVM) is a supervised ML algorithm which can be used for both classification and solving non-linear regression problems [48]. Support vectors are simply the coordinates of individual observations plotted on a high-dimensional space. SVM which is a decision plane/line segregates the two sets of data that belongs to different class memberships. SVM essentially consists of an optimizer algorithm and a kernel function. First, the given labeled training data (supervised learning) is projected into a high-dimensional space using the kernel function and then, the algorithm outputs an optimal hyper plane that best fit the data. Different SVM algorithms use different types of kernel functions. The objective of the optimizer algorithm is to find the optimal separating hyperplane usually represented by a function $F(x)$ and maximizes the margin between the two separating data classes. A detailed overview of the SVM approach is provided by Chalal et al. [49]. The algorithm was first presented by Boser et al. [50], in a computational learning theory conference in 1992. Since then, it is extensively used in numerous applications because of its accuracy and superiority. The accuracy can further be improved by using the optimization technique. Zhao and Magoulès [51] developed a simulation model using a Gaussian kernel function to predict energy consumption in buildings. Support Vector Regression (SVR) is the common version of SVM which uses the same principles as the SVM for classification, with only a few minor differences. It is a regression algorithm and is used for working with continuous values instead of classification which is SVM. Li et al. [52] predicted hourly electricity load of a residential building using weighted multi SVR model. The results were compared with neural network solutions which concluded that the proposed method performs better than the traditional solutions. ML-based energy consumption modeling techniques have two main limitations. First and bigger challenge is the amount of computing time that they take to train the networks. Computationally, a building SVM model is indeed more expensive and difficult. To explain a systems' behavior, it is important to know the processes that occur in a model. ML models act as a black-box and produce an output without being able to explain how the results are produced. The result can, however, be fine-tuned, but there is no access to the exact decision-making process. Secondly, ML-based prediction models rely on training data and may not perform well outside their training data range. For example, if any change is applied to the same building envelope, retrofit, adoption of new technology or even occupancy change, the



algorithm needs to be trained afresh.

D. Hybrid Approach

The hybrid model is a mixture of both deterministic and stochastic. Therefore, hybrid models used in the built environment for energy performance analysis employ both top-up and bottom-up approaches to overcome the limitations of both the approaches. The inputs that contribute strongest to the uncertainty in the output are treated stochastically using machine learning algorithms while the components that do not contribute significantly are treated deterministically with the help of physical models [55]. Tuhus-Dubrow and Krarti (2010) coupled simulation engine (DOE-2) with a genetic algorithm to determine the most efficient dwelling shapes for 5 different US climatic zones [56]. A new modeling approach has been developed by Hygh et al. [57] developed a flexible multivariate linear regression model using EnergyPlus to quantify buildings energy performance during the initial design stages. The model can be easily modified to account for any changes that are applied to the building envelope to optimize the design for greater performance.

VI. CONCLUSIONS

Energy performance modeling and quantification of energy consumption in buildings has become a significant tool for making decisions in enhancing energy efficiency and reduce energy consumption. It can precisely quantify the energy savings as a result of any energy conservation initiative introduced in the building. The rising concerns about increasing energy demand and GHG emissions have led to several initiatives and model development for building energy performance and consumption forecasting. However, accurate performance analysis for built environments is still a challenge. There is a significant gap between the reality and the simulated results due to a large number of parameters involved, input uncertainty, precise quantification and measurement of inputs, and highly stochastic nature of certain inputs such as end-users and occupancy schedule. Different approaches are used to characterize the energy performance of models. However, it is still difficult to assess the numerous models, their features and to select the most convenient one for the purpose. Different models have a different structure, features and use different data sets for energy performance modeling and consumption forecasting in the building sector. They have their strengths and weaknesses and perform differently under different conditions. A comprehensive analysis of different models presented in this paper along with their classification and suitability indicates that it is difficult to find a single model that can be used under all conditions universally. To develop or select an appropriate model, it is necessary to consider its structure, the relationship between the input and output variables and its applications. The study also defines the research gaps and provides directions for future studies, advances and research in the area of sustainable built environment.

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