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Review Article

Integrating Artificial Intelligence with Building Information Modeling (BIM) for Predicting Energy Consumption in High-Density Urban Hospitals: Review

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Abstract

Due to their unique requirements and complexity, hospitals have a big influence on global energy usage trends. For this inquiry, a comprehensive review of the literature was conducted. The analysis concludes that while a wide range of data inputs influence energy prediction, weather and occupancy data are particularly significant predictors. However, a number of studies failed to fully analyze the implications of the data they chose, revealing gaps in our understanding of time dynamics, operational status, and preprocessing methods. Interpretability and processing demands were among the difficulties with machine learning, despite its potential, particularly with regard to deep learning models like artificial neural networks. Our analysis showed that in order to improve prediction accuracy, more comprehensive daily activity data and a wider variety of meteorological inputs are required. It was discovered that sophisticated feature engineering and data preparation methods were necessary to enhance model performance. Future studies should focus on long-term energy forecasting and integrating real-time data into Intelligent Energy Management Systems for total sustainability in healthcare institutions. It was also acknowledged that improving model interpretability and investigating hybrid optimization techniques were necessary to expand the use of AI in this area. Future studies can greatly aid in the development of more effective and sustainable hospital energy management procedures by tackling these issues. The results show how AI has a lot of potential to optimize hospital energy use, but they also show how much more thorough and in-depth research is required.

Keywords: *Artificial Intelligence, Building Information Modeling, Hospitals.*

1. Introduction:

Hospitals are complex structures with unique requirements, setting them apart from other large buildings. Modern medical equipment, ventilation systems, and strict hygiene standards are some of the specific requirements for these hospitals (Xue *et al*., 2020). Complex (heating, ventilation, and air conditioning) systems must operate constantly due to hospitals' significant needs, which increases building energy consumption overall (Coccagna *et al.,* 2017). A study in England found that the hospital and allied services sector was responsible for a stunning 40% of the country's greenhouse gas emissions (Panagiotou and Dounis, 2022). Given the substantial potential to reduce carbon emissions and promote sustainable development goals, hospitals are now a critical area to focus on increasing energy efficiency. Therefore, in order to achieve significant economic and environmental benefits, hospital energy consumption reduction must be given top priority.

According to Abdel-Aal and Radwan (2004), load forecasting offers crucial insights for building and facility management, with lead periods varying from minutes to days and months. It has been demonstrated that this facet of energy management significantly affects energy optimization in large structures, including hospitals (Dagdougui *et al*., 2019). Additionally, precise For Smart Grid Management to effectively regulate network balance, projections of power exchange between on-site renewables and the main power grid are essential. This becomes particularly important in micro grid configurations, which are expected to play a major role in power systems in the future.

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For instance, a 2016 study demonstrated that a modest 5% mean absolute percent mistake in energy demand forecasts can lead to a large amount of unmet demand in aggregated energy systems where intermittent renewables play a significant role. Predicting building load demand has advanced significantly over the past ten years, which has spurred a lot of research in this area. This led to various models being proposed to accommodate for real-world applications (Amasyali and El-Gohary, 2018). According to ASHRAE, there are two types of building energy forecasting models as outlined by (Olu-Ajayi *et al.,* 2022): physics-based and data-driven.

Physical models are based on physics and engineering theories forecast and simulate load demand (Cao *et al*., 2020). This model considers building design, construction materials, thermal qualities, and weather to simulate in use energy consumption (Wang *et al*., 2019). To this end, several prominent building energy modeling applications have matured. Compared with other tools, some examples include Transient System Simulation Tool (TRNSYS), Environmental Systems Performance Research (ESP-r), Quick Energy Simulation Tool (eQuest), Energy Plus (Bui *et al.,* 2020) This kind of physical models includes a lot of heating, ventilation, air conditioning (HVAC) system specifications, insulation thickness, thermal characteristics, interior occupancy loads, solar data and other available data showing how relevant buildings' energy consumption, Because of these stringent restrictions, physical models are better suited for buildings in the design phase than as-built structures (Shao *et al.,* 2020).

Now, data-driven models are in place, as they use artificial intelligence to find connections between given inputs and desired outputs. Therefore, their popularity is growing rapidly: Such types of models are easier to implement, more flexible, and more accurate when predicting results. Besides, they can handle complicated data and are applicable in a broad scope of applications. Neural network integration is especially beneficial when developing models that will predict performance of ground coupled heat pump: Such a model can be up to seventeen times more accurate and efficient. The primary advantage of that method is that it is not appropriate to use the physics-based model when modeling these processes and the data-driven version is better because significant amounts of data are easily obtainable. In this case, data that can be used in the development of the model is the exact value of energy consumption by the building, weather data, time parameters, occupancy rate, and so on (Wang *et al.,* 2019). In addition, the required experiments can be run on available computer weather simulations.

In contrast, these factors play a more significant role in the hospital setting where there is an ongoing demand for energy, particularly due to the continuous operation of technology A (Bagnasco *et al*., 2015). Although it is widely accepted that forecasting energy demand is vital, it has not been systematically reviewed with respect to hospital buildings with a particular focus on new artificial intelligence (AI) approaches. Recent studies demonstrated the great potential of artificial intelligence (AI) to improve building energy prediction through sensor data analysis, demand pattern modeling and consumption profiling (Dagdougui *et al.,* 2019). But these ambitions involve creating a novel deep learning and machine learning means. A relevant example is the forecasting of GHP systems by using ANN and statistical pre-processing which showed a better forecasting performance that may be beneficial for hospital energy systems (Esen *et al.,* 2008). While AI and related data science applications are progressively working their way towards reducing global energy usage and greenhouse gas emissions, there is a notable gap in the literature for energy prediction in a hospital setting.

The primary aim of this study is to provide an extensive literature review on the implementation of AI approaches within healthcare setups along with the existent research gaps.

For financial and environmental reasons, hospitals must optimize their energy use. Hospitals must switch from outdated approaches to cutting-edge AI-based strategies for improved energy management as the globe becomes more conscious of sustainable practices. Although artificial intelligence (AI) and related technologies have advanced significantly to support building operations, their function in hospitals is still unknown. This study attempts to close that knowledge gap by investigating the application of various AI techniques, their effectiveness, and the complexities of energy consumption prediction in healthcare settings. By looking at how various AI techniques are used, we intend to shed light on how AI may assist hospitals in anticipating their energy use and direct research to provide the solutions required to increase energy efficiency and lower hospital carbon emissions.

2. Building Information Modeling (BIM) Technology:

The foundational element of BIM is the creation of a virtual building model, which provides a single, all-inclusive, and logically connected building information collection (Tang, 2019). In addition to providing geometric data, professional attributes, and status data that characterize building components, this data collection also includes status data about items that are not made up of components. Knowledge from building design and construction to operation and maintenance can be incorporated into the data. Library mentioned above, which will ultimately lead to the construction unit's implementation. Effective coordination between employees of the facility operating department, owners, and other parties is crucial to increasing job efficiency and reducing costs. As seen in (Figure 1), the BIM can be separated into three primary categories: technology, procedure, and policy. These three disciplines work together to create a framework that enables the digital management of building data during the architectural design and construction stages.

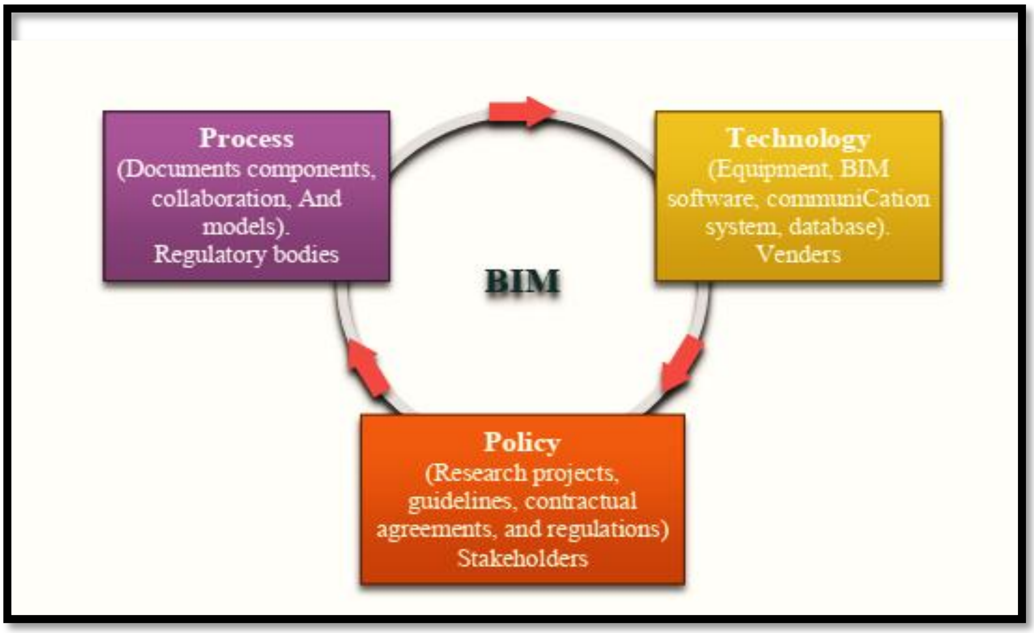

Figure (1): The Three Main Fields in Building Information Modeling

3. Artificial Intelligence (AI) Technology:

AI's ability to learn, adapt, and make decisions on its own will change the building company. Design, planning, construction, operation, and maintenance all make use of AI technology to enhance workflows, resource management, and the intelligence of urban structures. The development of smart city buildings depends heavily on AI's capacity to evaluate vast datasets and make inferences.

A branch of artificial intelligence called machine learning algorithms aids systems in pattern recognition, event prediction, and learning from actual data. This ability maximizes construction schedules, reduces expenses, and maintains urban projects (Nawaz, 2022).

The examination of the features of BIM and AI technologies that were previously covered shows unequivocally that Internet of Things (IoT) technology has the capacity to perceive, gather, transmit, and monitor low-level information content. AI technology excels in the intelligent analysis and processing of information data when applied to commercial applications. The higher-level capabilities of BIM technology include information integration, user communication, information display, and management. By combining the three technologies listed above, a "closed-loop information flow" might be created during the building process. This has enormous application value in the process of engineering construction (Raza, 2021).

4. Integrated Smart Hospital Design Foundation Using Building Information Modeling (BIM) and Artificial Intelligence:

One of the most innovative trends in the digital transformation of the construction sector is intelligent building design combined with BIM and AI. Standardized digital building models are provided by BIM, a fundamental tool for building information management, and AI technology enables wise design choices. The industry's constant quest for effective, superior design is what led to the merging of these two technologies. While AI technology has advanced from data analysis to sophisticated design-assisted decision-making, BIM technology has progressed from basic 3D visualization to comprehensive models with rich semantic content (Emam, 2025). Together, they make it possible to optimize the design process, enhance building performance, and encourage the shift in building design from conventional empirical decision-making to data-driven intelligent decision-making.

5. Critical technologies for BIM and AI integration:

5.1 Information Exchange Technology and BIM Data Structure:

The creation of multi-dimensional building models with both geometric and non-geometric data forms the foundation of intelligent building design, which is based on BIM data structures. In order to facilitate information interchange between disparate systems, modern BIM systems use object-oriented data architecture, define building elements as intelligent objects with parameterized attributes, and support standardized formats like IFC and gbXML (Li, 2012). Among the data exchange technologies, the middleware technology resolves the issue of data format conversion, while the RESTful API interface enables real-time data flow between the BIM platform and external AI systems. Distributed BIM database technology based on cloud computing efficiently manages vast amounts of data in large-scale projects and can increase data processing efficiency by 47% on average (Amer, 2023).

5.2 AI Algorithm Application Technologies in Architectural Design

AI's use in architectural design has progressed from a basic auxiliary tool to a comprehensive intelligent solution. In particular, generative adversarial networks may generate innovative and standard-compliant building solutions based on design conditions, demonstrating the effectiveness of deep learning algorithms in building form production. The best dynamic line scheme can be automatically generated in spatial layout optimization by combining the reinforcement learning algorithm with the building functional requirements and human flow simulation analysis. Experimental results demonstrate that this method's planning efficiency is 35% higher than that of the conventional approach, as illustrated in (Figure 2). A scientific foundation for energy-efficient design is provided by the recurrent neural network model's prediction accuracy of 93.7% in the field of building energy consumption prediction when combined with meteorological data (Wang *et al*., 2022).

Convolutional neural network technology is used for building component identification and classification, achieving a 96% recognition rate in intricate BIM models and significantly cutting down on model error checking time. Conversely, knowledge mapping technology creates a knowledge base for architectural design by tying together design specifications, past cases, and material performance data. This enhances architectural design intelligence overall and offers thorough knowledge support for AI decision-making (Edirisinghe and Woo, 2021).

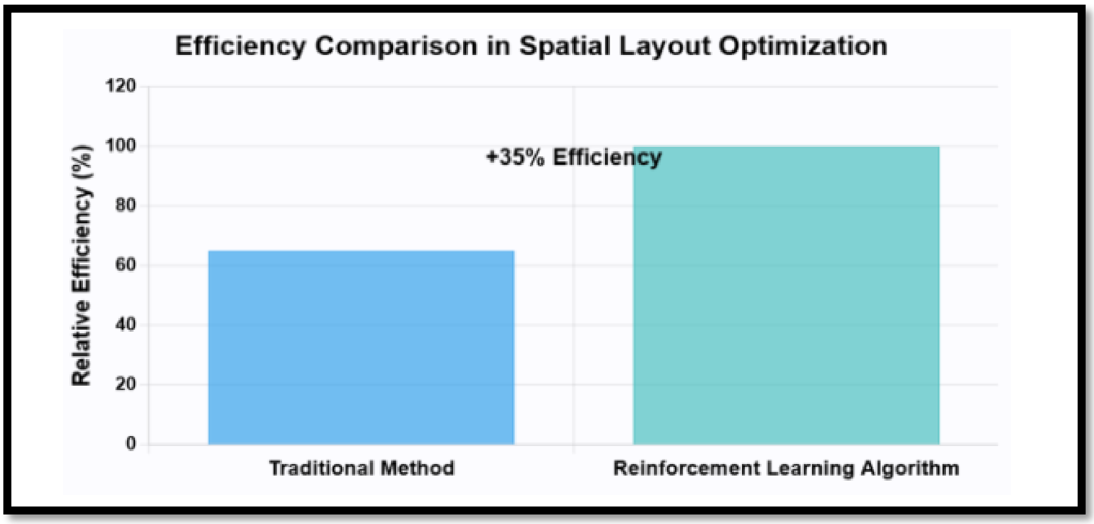

Figure (2): Comparison of efficiency in space layout optimization

6. The Approach

The goal of this study is to provide a thorough literature assessment of works that forecast hospital building energy use using data-driven techniques. Our objective is to offer a thorough comprehension of the state of AI techniques for hospital energy forecasting. Examining how different inputs, such occupancy, external temperature, and humidity, affect energy prediction models is one of the study's main components. We will also examine the nuances of data pretreatment techniques, compare various AI approaches, and talk about the implications of model parameters and hyperparameters

We offer a coherent and well-organized summary of the information gathered, emphasizing the relationship between hospital energy optimization, artificial intelligence, and machine learning settings. Also, to find best practices, common problems, and potential avenues for future research by examining the many approaches and results documented in the literature. Our goal is to contribute to the development of more sustainable and efficient energy management procedures in healthcare facilities by comprehending the specifics and potential of AI techniques. This study emphasizes how crucial it is to use cutting-edge technologies to make healthcare facilities more energy-efficient and environmentally friendly, which will help the healthcare sector as well as the environment.

7. Discussion Research Results:

7.1. Changes in energy forecasting throughout time

Depending on the time horizon taken into consideration, energy forecasting has several uses. Predicting the energy demand for the next few minutes, hours, or days is the main goal of short-term forecasting. It is important because it makes it possible for distribution businesses to optimize grid changes in accordance with market demands, power generation companies to coordinate production operations with those demands, and purchasers to plan their purchases for the best pricing (Sarkis-Onofre and Catala-Lopez, 2021). Short-Term Energy Forecasting (STEF) is important in many areas of the energy sector, in fact. First of all, it makes the optimal unit commitment easier, allowing power generation businesses to decide which units to commit to production based on the anticipated demand for electricity (Hong, and Fan, 2016).

Additionally, STEF helps manage spinning reserves, which are extra power generation capabilities kept on hand to react rapidly to unforeseen outages or abrupt spikes in demand. Managing the spinning reserves effectively is feasible based on precise short-term forecasts enabling them to be present at the right moment and used only if necessary, minimizing mash consumption and its costs (Raza and Khosravi, 2015). STEF also helps assess contracts for sales or purchases among firms doing business with various energy markets. Accurate and timely forecasting of energy demand provide businesses with the opportunity to maximize their purchases and sales to meet the projected demand of markets. This enables them to negotiate contracts based on trustworthy predictions (Fernandez-Martínez *et al.*, 2022). For medium-term forecasts, the aim becomes estimating electricity consumption for the following weeks or months. Medium-Term Electrical Energy Forecasting (MTEF) is a vital factor for the optimization of large-scale power system infrastructure maintenance and operation (Bekteshi *et al.,* 2015). By predicting energy consumption demand in a more accurate way, MTEF supports businesses and government organizations in balancing production schedules, capacity planning and resource use against market requirements. This optimization ensures neither overproduction nor underproduction and thus increases profitability and productivity (Fernandez-Martínez *et al*., 2022). MTEF also facilitates the enhancement of operating efficiency, reduction of interruptions and maintenance planning. In addition, it provides the concept of positive fuel supply, making sure of a continuous and dependable supply to maintain its operation without operational interruptions (Fernandez-Martínez *et al.,* 2022). MTEF strategy may help organizations to evaluate the feasibility and economic viability of renewable energy technologies adoption into the energy portfolio by live capacity expansion planning of these technologies. In this way, MTEF enables companies to make informed decisions, improve their energy performance, and move toward sustainability (Fernandez-Martínez *et al*., 2022).

Finally, the ultimate aim of long-term forecasting is to predict the annual energy demand and peaks for subsequent years (Timur et al. 2020) Long Term Energy Forecasting (LTEF) plays a fundamental role in power system planning in long term and it is compatible to a future energy demand of a country and regulations. It provides critical information about expected long-term trends in energy demand which helps Utility Corporations, lawmakers, and energy regulators make informed decisions (Fernandez-Martínez et al., 2022). By forecasting long-term energy demand accurately, LTEF aids in identifying potential energy supply gaps and the infrastructure adjustments that will be needed to accommodate them as demand grows. This data facilitates planning for the entire power system considering transitional energy landscape (Timur *et al.,* 2020).

7.2 AI methods for predicting energy:

Zor et al. (2020) cite a number of applications for machine learning and one being forecasted energy consumption. Machine learning techniques have been researched in this area to enhance the accuracy of predictions. Abstract:Machine learning is motivated by the computational force that provides machines the ability to learn from data, which is to learn patterns and generate accurate predictions about the future (Nakai et al., 2021). UID research has relied on a variety of algorithms, with high computational models such the deep neural network and lower computational regression models such as Multiple Linear Regression (MLRM) as well (Zini and Carcasci, 2023). Many papers compare several strategies, emphasizing the pros and cons of the given algorithms. Methods like Principal Component Analysis (PCA) and Orthonormal Partial Least Squares (OPLS) have successfully provided those techniques for high dimensional datasets. These methods allow a better approach of the forecasting through the elimination of noise and the direct detection of key seasonal and trend components (Gordillo et al., 2018). In addition, combining PCA and OPLS predictions using ensemble methods has been found to reduce predicting errors due to the counterbalance of the overestimate/underestimate tendency (Gordillo et al., 2018).

Even though this is fewer novels, methods like Multiple Linear Regression (MLR) have been utilized extensively for these initiatives, even though MLR has limitations when dealing with complex datasets. Due to the limitations of MLR, more sophisticated techniques like ANNs (Zini and Carcasci, 2023) have been developed and improved. While MLR provided significant insights, ANN emerged as the better forecasting method in these two comparisons, especially due to the ability to identify different morning and afternoon energy usages. Moreover, Random Forest and Ada-Boost have been able to cope with the variance in energy utilization over different periods, e.g., weekdays against weekends and seasonality (Xue *et al.,* 2022). Even though time series based on periodic trend modeling may not be the only method available for this type of problem, it is also likely that a hybrid approach integrating multiple models/methods is needed, because predicting energy is a complicated process. Ensemble techniques have been developed to combine these models which include but are not limited to, extreme gradient boosting (XGBoost), random forest (RF) (Cao *et al,* 2020). Ensemble methods are, after all, based on collective intelligence, oftentimes giving more specific predictions. Hybrid models that use the Grey Wolf Optimizer (GWO) to select features and Support Vector Regression (SVR) to fit the model have shown a better performance for hyper parameter adjustment in comparison to common machine learning models (Zini *et al.,* 2024). In addition to their design, the parameters of Bidirectional Long Short-Term Memory (BiLSTM) models play an essential role in their performance; furthermore, the Whale Optimization Algorithm (WOA) can be applied to these models to improve performance based on previous research in the use of architecture to address time-lag effects in predicting building energy consumption. Changing hyperparmeters, such as the learning rate, dropout rate, or the number hidden layers would significantly improve model performance (Nakai et al., 2021). Techniques such as grid search and cross-validation have been useful in the search for optimal hyper-parameters; so Random Forest and AdaBoost outperformed simpler models such as Decision Tree and Bagging (Xue *et al.,* 2022).

7.3 Healthcare buildings:

Healthcare buildings, which are a type of commercial structures, exhibit unique patterns of energy demand because they contain both general-purpose spaces and specialized medical units. Examining the literature reveals that researchers use a variety of data inputs. These data categories include operating status, occupancy, time changes, climatic inputs, and even the raw data that forms the basis of prediction models. Such variety implies that a thorough understanding of these factors is essential for making accurate predictions about energy usage. It's interesting to note that while numerous researches clarify these factors, very few examine the complexities and ramifications of their decisions. For example, occupancy turned out to be a significant effect in hospital energy consumption. According to research, distinct days of the week or day types can be used as stand-ins for occupancy levels, representing trends in energy usage. Hospitals exhibit unique patterns of energy use on weekends and holidays as a result of fewer activities. But not every hospital activity uses the same amount of energy. For example, overall energy use may not be greatly impacted by admissions or crises. Therefore, to increase forecast accuracy, granular data must be examined, such as the sorts of residents or particular daily hospital operations. According to our research, hospital activity and energy consumption may be reasonably predicted by the day of the week (weekend, holiday, or weekday), but prediction accuracy can be further increased by including specific daily activity data, such as the number of in-patients and out-patients. This suggests that additional in-depth information regarding occupancy and its connection to energy use in hospital settings should be the focus of future research. Likewise, it is impossible to overstate the importance of meteorological data in energy consumption projections. For instance, the temperature outside is a reliable indicator of hospital energy use.

8. Conclusion:

It is crucial and difficult to forecast energy use in healthcare environments. Despite the fact that recent research provides valuable insights, many questions remain. Because different occupancy types, specific activities, and weather variables interact, energy prediction is challenging. As AI and machine learning advance, it is crucial to integrate more diverse and comprehensive data to improve prediction accuracy. Healthcare organizations can effectively employ AI to optimize their energy use.

In order to increase the precision of energy consumption forecasts, our work highlights the significance of taking into account comprehensive daily activity data as well as a broader range of meteorological elements. Refining models to accommodate the evolving nature of healthcare operations requires an understanding of these specifics. The linkages between everyday activities, seasonal variations, and the use of certain equipment make energy use prediction difficult, which presents intriguing opportunities for further study. To improve model accuracy and resilience, future studies should investigate hybrid optimization techniques and sophisticated ensemble approaches. Enhancing model interpretability is also essential for informing healthcare stakeholders about AI-driven predictions. Dealing with These sectors will provide healthcare facilities with the tools they need to effectively and sustainably manage their energy use.

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