The Application of Artificial Intelligence (AI) In Optimizing Energy Consumption in Real Estate Projects: A Review

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Abstract

This review focused on the application of artificial intelligence (AI) in optimizing energy consumption in real estate projects, it noted that the real estate sector is a major contributor to global energy consumption which accounts for approximately 40% of total energy usage. To cater for the above emerged Artificial intelligence (AI) which appears as a promising solution to optimize energy consumption in real estate projects. The review identified the AI technologies which include machine learning and deep learning, can also aid in the analysis of the complex data patterns, prediction of energy demand and optimization energy distribution. It noted that the integration of AI in energy systems has revolutionized the way we approach energy optimization and its management systems can help in energy consumption optimization, reduction of waste and costs and minimisation of environmental impact. The research noted that the benefits of AI-powered energy optimization are multifaceted which includes energy savings, reduction of cost as well as environmental benefits. It also identified challenges and limitations to such as ensuring data quality and availability, cybersecurity, its scalability and interoperability. The identified case studies also demonstrated the effectiveness of AI-powered energy management systems in smart buildings and cities. The review concluded that the adoption of AI-powered energy optimization can help the real estate industry in term of reduction energy consumption, costs and environmental impact while also in the improvement occupant comfort and sustainability.

Keywords

Artificial Intelligence, Consumption, Energy, Projects and Real Estate

1. Introduction

The real estate sector contributes significantly to the global energy consumption, while it accounts for approximately 40% of total energy usage, (Marques et al., 2024). As the world continues to battle with the challenges that is associated with climate change, the issues bothering on energy efficiency in respect to real estate projects has become a serious concern. The optimization of energy consumption not only reduces operational costs but also aids in the minimization of environmental impact, (Marques et al., 2024). The energy

efficiency in real estate is of great important and cannot be overstated, as it plays a major role that is aimed at reducing greenhouse gas emissions as well as mitigation of the effects of climate change, (Dinmohammadi et al., 2025).

It is worthy to note or state, that artificial intelligence (AI) has emerged as a promising solution aimed at optimizing energy consumption in real estate projects. AI technologies which include machine learning and deep learning can help in the analysis of complex data patterns, prediction of energy demand, as well as optimization of energy distribution, (Iluyomade & Okwandu, 2024). There appears much benefit through the adoption of AI, as in the case of real estate developers and managers it can help in the reduction of energy waste, lowering of operational costs and improvement on the overall sustainability of their projects.

There appears to be potential of AI especially in the optimization of energy consumption and this is seen as vast. Systems powered by AI can aid in the analysis of data from various sources such as sensors, meters and weather forecasts, in the prediction of energy demand and adjustment of energy supply, (Rojek et al., 2025). This no doubt will help real estate developers and managers in making data-driven decisions, optimization of energy consumption and reduction of waste.

This review focuses is on the provision of a comprehensive overview of the application of AI in terms of its optimization of energy consumption in real estate projects. It delves into the discussions on the various AI technologies that are often used for energy optimization, their applications in smart grids and smart buildings as well as the benefits including the challenges that are associated with their adoption.

Through the review of existing research on AI-powered energy optimization in real estate, this review aims at contributing to the development of more sustainable and energy-efficient real estate projects. It is expect that the findings from the review will highlight future research directions as well as provides insights into the potential of AI in shaping the future of energy-efficient real estate.

2. Literature Review

This literature review exploration is on the application of Artificial Intelligence (AI) in energy optimization that is driven by the ever-increasing demand for energy efficiency. It in addition examined the role of Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), while they all aimed at the optimization of energy consumption, prediction of energy demand and improvement of grid reliability. This review discussed the applications of AI in smart grids, smart buildings as well as predictive maintenance; it highlights the benefits of energy savings, reduction of cost and reduction of environmental impact. It also addressed the challenges such as data quality, cybersecurity and its scalability. It provided a comprehensive overview of the potential AI in the optimization of energy and its implications as it relates to sustainable energy management.

2.1 AI Technologies for Energy Optimization

Artificial Intelligence (AI) technologies integration in energy systems has revolutionized the way we approach energy optimization, (Icaza et al., 2025). In the case of prediction of energy demand and optimizing energy distribution Machine Learning (ML) plays a crucial role, (Cavus et al., 2025). ML algorithms have the potentials to analyse historical data and real-time energy usage patterns needed to forecast energy demand thus, it enables utilities and grid operators in the adjustment of energy supply, (Almeida et al., 2025). This approach helps in the reduction of energy waste, improvement of grid reliability as well as in the enhancement of the overall energy efficiency, (Chen et al., 2023).

The adoption of ML in the optimization of energy can enable the integration of renewable energy sources into the grid. ML algorithms can help in the prediction of the output of renewable energy sources such as solar and wind power thus, allowing grid operators to adjust their energy supply through the analysis weather patterns and energy demand, (Chen et al., 2020). This helps in a more efficient as well as reliable integration of renewable energy sources into the grid thus; it also helps in the reduction of reliance on fossil fuels and also in the lowering of greenhouse gas emissions, (Elalfy et al., 2024).

Deep Learning (DL) techniques in the case of its application to energy management have been useful to energy management. This includes predictive maintenance and forecasts of energy consumption. The DL models can learn complex patterns in energy usage data thus, its enables the accurate predictions of energy demand and potential failures that may come from the equipment, (Almeida et al., 2025). This allows for proactive maintenance and helps in the reduction of downtime thus, resulting to an improvement in energy efficiency and cost reduction.

Deep Learning (DL) techniques have changed energy management by providing accurate predictions and insights. These tools support proactive decision-making. In energy management, DL models are especially useful for predicting maintenance needs and forecasting energy use. By examining complex patterns in energy data, DL models can forecast energy demand and potential equipment failures, (Mingotti, 2025). This allows for timely maintenance and lowers downtime. As a result, energy efficiency improves, and costs decrease.

One of the main advantages of DL in energy management is its ability to analyze large datasets, (Ardabili et al., 2022). It identifies patterns that might not be obvious through traditional methods. This allows DL models to predict energy demand with great accuracy. Energy managers can then make better choices about supply and demand. Further, DL models help spot potential equipment failures, letting maintenance teams act before issues arise and minimizing downtime, (Mingotti, 2025).

DL techniques like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks work well for energy forecasting, (Mingotti, 2025). These models learn complex patterns in energy usage data and accurately predict future energy needs, (Raffoul et al., 2024). Convolutional Neural Networks (CNNs) can also assist in energy forecasting, especially with large datasets, (Aguiar-Pérez & Pérez-Juárez, 2023).

The benefits of applying DL in energy management include better energy efficiency, lower costs and greater reliability, (Aguiar-Pérez & Pérez-Juárez, 2023). By forecasting energy demand and potential equipment issues, DL models help managers optimize supply and demand, (Mingotti, 2025). This reduces waste and enhances overall efficiency. Moreover, DL models can lower maintenance costs by identifying potential equipment problems, allowing for proactive upkeep, (Mingotti, 2025).

Besides predictive maintenance and energy forecasting, DL can also support other energy management tasks, like energy optimization and detecting anomalies, (Mingotti, 2025). For example, DL models can optimize energy use in buildings by highlighting inefficiencies and offering suggestions for improvement, (Tsallis et al., 2025).

The use of DL techniques in energy management could change how one handles energy systems, (Liu & Chen, 2025). By offering precise predictions and insights, DL models assist managers in optimizing supply and demand, cutting costs, and boosting efficiency, (Ardabili et al., 2022). As technology advances, one can anticipate more innovative uses of DL in energy management, driving greater efficiency and sustainability in the energy sector.

The implementation of DL in energy management may notably affect the development of smart grids and smart buildings, (T et al., 2024). With accurate predictions and insights, DL models can help grid operators and building managers optimize supply and demand, reducing waste and improving efficiency, (Miraftabzadeh et al., 2021). DL models can pinpoint potential security threats and anomalies, enabling proactive measures to avoid disruptions, (Nicolas et al., 2025).

Reinforcement Learning (RL) is a form of machine learning that has gained popularity in recent times; this is due to its ability aimed at enabling agents to learn from their environment and make decisions that aids in the maximization of a reward or minimization of a penalty, (Khezeli et al., 2023). Hence, one can affirm that Reinforcement Learning (RL) has shown its huge potentials in the optimization of energy distribution and management of grid. There is no doubt that its application in the optimization of energy consumption in real estate projects is a good example of its potential, this is particularly true as RL algorithms can be used in the analysis data from various sources such as the sensors, meters and weather forecasts aimed at optimising energy consumption in buildings, reduction of energy waste and costs, (Rojek et al., 2025). This is in addition to improving occupant comfort and sustainability. RL can help property managers and owners in the reduction of their energy bills, minimisation of their carbon footprint and contribute to a more sustainable future through the learning of the patterns and preferences of building occupants and adjusting energy usage, (Almeida et al., 2025).

RL can also be used in optimising energy consumption in various types of properties which include commercial, residential and industrial, (Yu et al., 2021). This can also be integrated with other technologies such as building management systems (BMS) and energy management systems (EMS) in order to provide a comprehensive solution for the optimization of energy, (Hossain et al., 2023). The benefits of RL in the optimisation of energy consumption make it an emerging area for research and development even while there are still challenges affecting the implementing RL in real estate projects which includes; the quality of data and its availability, the complexity of algorithm and its interpretability. While the real estate industry continues in the way it evolves and continues to prioritize sustainability, the need of RL in the optimisation of energy consumption is more likely to gain significance. In effect it will enable building owners and property managers in their bid to reduce energy consumption, lower their costs as well as contribute to a more sustainable future.

While we continue to witness advances in technology, one may expect to see more innovation in the applications of RL in real estate and other sectors thus driving greater efficiency, its sustainability as well as innovation. The application of RL in the optimisation of energy consumption in real estate projects is another potential area of research which has the opportunity aimed at transforming the way one design, operate and manage properties.

2.2 Applications of AI in Energy Efficiency

The has been an appreciable level of transformation in the way people approach energy efficiency, this is courtesy of the integration of Artificial Intelligence (AI) in energy systems. AI's applications can be seen in the area of energy efficiency, smart grids and buildings as well as predictive maintenance.

In the area of smart grids, AI plays a critical role in the management of energy distribution, the prediction of energy demand and the optimisation of grid operations, (Balamurugan et al., 2025). The AI algorithms can help in the analysis real-time data from smart meters, forecasting of weather and the pattern of energy usage to the prediction of energy demand and adjustment of energy supply, (Judge et al., 2024). This helps in the efficient distribution of energy, reduction of energy losses and improvement of grid reliability, (Nutakki & Mandava, 2024).

The ability to predict energy demand in real-time is one of the key benefits of AI in smart grids, (Arévalo & Jurado, 2024). Through the analysis of smart meters data as well as from other sources, AI algorithms can identify the patterns and the trends in the use of energy thus, enabling utilities in their adjustment energy supply, (Olawade et al., 2024). In the peak demand period, they can be reduction, alleviation of strain on the grid and prevention of power outages.

AI can also be useful in the optimisation of grid operations through the identification of areas of inefficiency and provision for recommendations for improvement. Through the analysis of data gotten from sensors and other sources, there can be opportunities for the identification of energy savings and provision of recommendations for grid optimization courtesy of AI algorithms, (Rojek et al., 2025). This will help utilities to in making data-driven decisions and optimisation of grid operations for maximum efficiency. Renewable energies such; as solar and wind power can be integrated into the energy sources courtesy of AI. Through the analysis of weather forecasts and energy harvesting patterns, it is possible for AI to predict the output of renewable energy sources and adjust energy supply accordingly, (Olawade et al., 2024).

In smart buildings, AI is very useful in the optimisation of energy consumption, management HVAC systems and improvement of building energy efficiency. The analysis of data from sensors, meters useful for identifying energy-wasting areas and optimisation of energy usage are all possible courtesy of AI-powered systems, (Iluyomade & Okwandu, 2024). AI can help in the control of HVAC systems thus helping in the optimisation of heating and cooling, reduction of energy consumption and improvement of occupant comfort.

Another key application in energy efficiency is AI-powered predictive maintenance. Predictive maintenance uses is said to be using machine learning algorithms in the analysis of data from sensors and equipment in the prediction of potential failures and scheduling of maintenance accordingly, (Simion et al., 2024). The benefit is that it reduces downtime, helps in the improvement of equipment efficiency and minimisation of energy waste, (Aminzadeh et al., 2025). AI-powered predictive maintenance can aid in the improvement of grid reliability and reduction of the likelihood of power outages through the prediction and prevention of equipment failures, (Patil, 2025).

2.3 Benefits and impact of AI in energy optimization

There appears to have been a significant potential in the optimization of energy consumption, reduction of costs and minimisation of environmental impact courtesy of the integration of Artificial Intelligence (AI) in energy systems. Its optimization appears to be multifaceted and they range from energy savings to reduction of cost and environmental benefits.

Energy Savings:

There can be energy saving courtesy of AI-powered energy optimization and through the analysis of energy usage patterns, prediction of energy demand and optimisation of energy distribution. Studies in the past have shown that AI-powered energy optimization can aid in achieving energy savings of up to 20% in commercial properties and 15% in industrial properties or buildings, (Iluyomade & Okwandu, 2024). AI-powered building management systems can help in the optimisation of heating, cooling and its lighting systems, reduction of energy consumption and improvement of occupant's comfort, (Aghili et al., 2025).

Cost Reduction:

There appears to be significant cost benefits courtesy of AI-powered energy optimization. Through the optimisation of energy consumption and reduction of energy waste, AI can help the utilities and grid operators in the reduction of their operational costs, (Rojek et al., 2025).

Also, through the identification of the potential equipment failures and scheduling maintenance AI-powered predictive maintenance can help in reducing maintenance costs. This is believed to help in the extension of the lifespan of equipment, reduction of the need for costly replacements. Hence in a study by, (Patil, 2025), AI-powered predictive maintenance can in the reduction maintenance costs by up to 30% in industrial sector.

Environmental Impact:

It has said that the environmental benefits of AI-powered energy optimization are appreciable. Through the reduction of energy consumption and optimisation of energy distribution, AI can help in the minimisation of greenhouse gas emissions and mitigation of the impacts of climate change, (Alghieth, 2025). AI is believed to also help in the integration of renewable energy sources into the grid. It can help in reduction of reliance on fossil fuels as well as in the promotion sustainable energy development, (Vinuesa et al., 2020). Studies in the past have shown that AI-powered energy optimization can aid in the reduction of greenhouse gas emissions by up to 10% in commercial properties/buildings and 5% in industrial settings, (Rojek et al., 2025). If AI-powered energy optimization is adopted, there appears to be more benefit as it can help in the reduction of our environmental footprint and promotion of sustainable energy development.

2.4 Challenges and limitations of AI-powered energy optimization

There is no gainsaying the fact that the integration of Artificial Intelligence (AI) in energy systems has over the years shown huge potential in the optimisation of energy consumption, reduction of costs and minimisation of environmental impact. In spite of these huge potentials there are still several challenges and limitations that need to be addressed in order to fully harness its potential, the challenges are as discussed below;

Data quality and availability:

The importance of high-quality data has been identified as one of the primary challenges of AI-powered energy optimization, (Billanes et al., 2025). AI algorithms require not only large amounts of accurate but reliable data in learning of patterns, prediction of energy demand and optimisation of energy distribution, (Olawade et al., 2024). It is also a known fact that poor data quality can lead to biased models, result to inaccurate predictions as well as suboptimal energy optimization. It is important to state that ensuring the quality and availability of data is very necessary for AI-powered energy optimization, (Adhikari et al., 2024). This can be achieved through the implementation of a robust data collection and validation processes hence ensuring the integrity data available while addressing data gaps, (Lin et al., 2025).

Cybersecurity:

Cybersecurity is another clear challenge that is prevalent with AI-powered energy systems. While AI increasingly becomes a critical part to the energy systems, there is definitely going to be increased risk of cyber-attacks and data breaches. It is well known fact that cyber-attacks can actually compromise the integrity of AI models leading to disruption in energy distribution or even physical harm, (Nicolas et al., 2025). It is therefore imperative to state that ensuring the cybersecurity of AI-powered energy systems is of huge important. This issue cybersecurity of AI-powered system can be achieved through the implementation of a robust security protocols, encryption of data and conduction of regular vulnerability assessments, (Roshanaei et al., 2024).

Scalability and interoperability:

The scaling of AI-powered energy optimization solutions and ensuring its interoperability with existing systems is yet another significant challenge. While AI-powered energy optimization solutions are deployed say in different regions and industries and ensuring the possibility of potential scaling to meeting the growing demands and integration with existing systems becomes critical, interoperability issues can on the order hand arise due to the differences in the formats data came, the communication protocols as well as system architectures, (Albouq et al., 2022). It will be of interest to note here that the development of standardized protocols and frameworks for AI-powered energy optimization solutions can help in ensuring seamless integration and scalability, (Rojek et al., 2025).

3. Case studies, examples and discussions

Case study 1: AI-powered building management system in Singapore

In Singapore was what they smart building for mixed development precinct. The report about this innovation came to lime light in 2023 published by Switzerland's Institute for Management Development (IMD). The noted that by integrating technologies such as IoT, data analytics and AI, Singapore has transformed the urban landscape, creating more comfortable and livable spaces for residents and businesses.

The Building and Construction Authority (BCA), in a report by Switzerland's Institute for Management Development (IMD) reported that buildings in Singapore have reduced their energy consumption by 16% on average through the adoption of energy-efficient practices, including the use of smart technologies. This is according to

This case study featured a mixed (Commercial towers, Retail mall and residential blocks), development precinct project that has achieved the esteemed Green Mark Platinum rating, and is dedicated to sustainability and energy efficiency. Operating as a Smart Precinct through the Open Building System Integration (OBSI) platform, it seamlessly integrates building systems and equipment. The projects' specific goal was to provide a modern and efficient environment for tenants, building management teams and contractors. This innovation was powered by Open Building System Integration (OBSI) platform and iviva software, they connected air conditioning, electrical, fire, car park, CCTV, lift, access control and people counting i.e. Integrated them with 3D BIM models created a Digital Twin of each building and the precinct, enabling smart operations and maintenance. The benefits were highlighted as follows;

1. Tenant Empowerment: Advanced technology and services provide tenants with enhanced experiences and convenience.
2. Sustainable and Energy- Efficient Buildings: Promotes energy efficiency and sustainable practices, contributing to Green Mark Platinum rating.
3. Lean Implementation: Streamlined operations and automated processes improve efficiency.
4. Quality Assurance: The Digital Twin ensures the quality of systems and processes for optimal performance.
5. Smooth Handover: The iviva Commission to Operate (C2O) process simplifies delivery and ensures an operationally ready system.
6. Reduced Maintenance Costs: Predictive, condition-based maintenance minimises costs and maximises system uptime.
7. Management by Exception: Dynamically assembled operational dashboards enhance critical alarm management and exception-based decision making.

8. Lifecycle Management: Efficient management of the building's life cycle, from construction to operations.

The successes recorded were;

- Integration of BIM and building systems to create a Digital Twin for smart operations and maintenance.
- Successful validation of the C2O process for delivering an operationally ready Digital and Physical Twin.
- Utilisation of the Digital-Physical Twin model for smart operations, maintenance and tenant services.
- Achieving Green Mark Platinum rating.
- Implementing smart security, surveillance and incident management with intelligent process automation.

Case Study 2: Predictive Maintenance and AI

Devarajan (2025) in a study; advancing data center reliability through AI-driven predictive maintenance stated that the evolution of data center maintenance has undergone a transformative shift from what used to be a traditional reactive and scheduled maintenance to AI-driven predictive maintenance strategies. The study noted that the integration of artificial intelligence and machine learning technologies enables precise failure prediction, helps in the optimisation of resource allocation and enhancement of operational reliability. Here, advanced sensor networks and sophisticated analytics pipelines process vast amounts of operational data, while machine learning models which neural networks, support vector machines and decision trees did a good job through the provision of accurate predictions of component failures. The framework for the implementation features the system integration, data management, and development of model as well as operational integration thus leading to substantial improvements in the maintenance of efficiency, reduction of cost and equipment longevity. Devarajan (2025), further stated that the convergence of human expertise with AI capabilities marked a clear advancement in predictive maintenance, it in addition revolutionised how organizations approach data center operations and reliability management.

Case Study 3: AI-Powered Energy Management in a Smart City

Smart city initiative in has been practice in many cities; According to Trivedi, (2024), the main technologies in smart cities are artificial intelligence (AI), machine learning (ML) and the (IOT) Internet of Things. Trivedi, (2024), in 10 Ways AI can be used in Smart Cities identified AI applications in smart cities, the summary is as follows;

1. Intelligent Traffic Management: Some Use Cases of Intelligent Traffic Management can be seen in Singapore, London and Los Angeles.
2. Smart Waste Management: Some Use Cases of Smart Waste Management are in Barcelona, San Francisco and Dubai.
3. Energy Management and Smart Grids: Some Use Cases of Energy Management and Smart Grids are Tokyo, New York City and Amsterdam.
4. Public Safety and Security: Some Use Cases of Public Safety and Security are Chicago, Rio de Janeiro and New Delhi.
5. Healthcare and Telemedicine: Some Use Cases of Healthcare and Telemedicine are Tel Aviv, Shanghai and Dubai.
6. Environmental Monitoring and Sustainability: Some Use Cases of Environmental Monitoring and Sustainability can be seen in Copenhage, Vancouver and Melbourne
7. Intelligent Transportation Systems: Some Use Cases of Intelligent Transportation Systems are found in Shanghai, Phoenix and Hamburg.
8. Infrastructure and Urban Planning: Some Use Cases of Infrastructure and Urban Planning are found in Singapore, Dubai and Barcelona.
9. Smart Governance and Citizen Services: Some Use Cases of Smart Governance and Citizen Services can be seen in Helsinki, Boston and Dubai.
10. Enhancing Connectivity and Communication: Some Use Cases of Enhancing Connectivity and Communication are found in Seoul, San Francisco and London.

4. Summary of key findings and implications for of AI-powered optimization for the real estate industry

Below is the summary of the key's findings;

1. AI-powered energy management systems optimise energy consumption, helps in the reduction of waste and costs as well in the minimization environmental impact through predictive analytics and machine learning algorithms.
2. Deep learning techniques such as neural networks and LSTM networks can predict energy demand accurately in addition to potential equipment failures thus, enabling proactive maintenance and reduction of downtime.
3. Reinforcement learning helps in the optimisation of energy consumption in buildings, reduction of energy waste and costs including the improvement of occupant comfort and sustainability via data-driven decision-making.
4. AI-powered predictive maintenance aids in the reduction of maintenance costs, extension of equipment lifespan and improvement of grid reliability through the identification of potential failures and maintenance scheduling.
5. AI-driven energy management systems can achieve energy savings to a much-desired level even up to 20% in commercial buildings and 15% in industrial buildings as well help in the reduction of greenhouse gas emissions.

There is no doubt and from the review that the real estate industry can benefit greatly from AI-powered optimization, particularly in the management of energy and predictive maintenance. Through the leverages on machine learning and deep learning techniques, property managers as well as owners can achieve the much-desired optimisation of energy consumption, waste reduction, and costs minimisation. The AI-powered predictive maintenance identifies potential equipment failures, helps in the reduction of downtime while extending lifespan. This in turn has leads to the saving of energy in a significant way, improvement of occupant comfort and reduction of environmental impact. Also, smart buildings and cities can be developed, while optimizing energy distribution and ensuring reliability of the grid. But it's important to note that there are still challenges which include ensuring data quality and availability, cybersecurity that is robust and scalable and interoperable systems.

5. Conclusion

Conclusively, AI-powered optimization has implications for the real estate industry; this is more noticeable in energy management and predictive maintenance. Therefore, it will be of utmost importance to leverage on machine learning algorithms and deep learning techniques. With this property managers and owners can optimize their energy consumption, reduce waste in energy as well as minimize costs. The benefits of AI-powered optimization make it an attractive solution for the real estate industry even though challenges abound. As the innovation in technology advances, one can expect to see more innovations in terms of applications of AI-powered optimization in the real estate industry that drives greater efficiency, sustainability and innovation.

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