# The use of AI for real-time energy management in buildings: An overview

**Abstract:**

This paper emphasizes the need for efficient energy consumption in buildings due to the increase in pollution and economic growth, which has led to an increase in energy consumption worldwide. Therefore, a real-time energy management system is needed to overcome the deficiency of energy consumption and improve energy efficiency. Further to adopt modern architecture, we introduce artificial intelligence; to identifythe factors involved in optimizing energy consumption in buildings is an important factor. The paper also suggests different machine learning (ML) based algorithms for data cleaning, processing, and analysis. This includes different studies that used AI-based techniques for real-time energy management systems, including reinforcement learning, rule-based approach, and mixed integer linear programming, to reduce energy consumption by 20%-30%. The use of AI in energy management in buildings holds great potential for world's scientific community.This technology enables data-driven decision-making, fosters energy conservation, and promotes advancements in the field of energy science, contributing to a greener and more sustainable future. The paper concludes that the use of AI-based approaches for energy-efficient systems can predict future energy demands by using previous data and building characteristics, making it more efficient than previous monitoring and alert systems.

**Keywords:** Artificial Intelligence, Real-time energy management, renewable energy, machine learning, natural language processing

**Introduction:**

In the 21$^{st}$ century, global energy consumption has seen strong growth from all parts of the world. The trends show that the consumption of energy will continue to increase due to an increase in pollution and economic growth. The continuous development of buildings needs a system where the energy should be used efficiently, especially where the supply of energy is less or has strict requirements. If we address energy consumption in buildings, according to the reports published by (IEA, 2020) buildings reported 39% of $CO_2$ emissions and 36% of global energy consumption. The energy problem in buildings comes to attention after the initiative and study of Go Green (2020) and China renew sustainable energy. To overcome the deficiency of energy consumption and improve energy efficiency, a real-time energy management system is required. This leads to the involvement of artificial intelligence in real-time energy management systems to decrease energy consumption in buildings. Lastly, implementing strategies to enhance energy performance in buildings promotes innovation, job creation, and economic growth. It drives the development of new technologies, materials, and construction practices, promoting a green environment and creating employment opportunities in the energy efficiency and renewable energy sectors.

**Main Text:**

The demand for energy consumption leads to a shift in the implementations toward the modern machine learning implementation for the latest development (Karpook, 2017). To introduce artificial intelligence, the identification of the factors that are involved in optimizing energy consumption in buildings is an important factor. Mirabella et al. (2018) discuss the various factors, which include the awareness between the different actors in the building industry, enhancement in building energy-efficient products, and betterment in development tools. It also focuses on the importance of implementing energy performance improvements measures in buildings to achieve sustainability goals. Energy-efficient buildings require less energy for heating, cooling, and electricity, resulting in reduced utility bills and operational expenses.

From the buildings, Marinakis, V. (2020) shows that data can be collected using sensors, IoT devices, smart devices such as meters, energy performance contracts and certifications, and from the management systems of the building. The author Pancholi et al. (2014) says that a million bytes of data are produced from the smart devices installed in the building to be controlled and handled accordingly for energy efficiency in future usage. After the collection of the data, it can process using different artificial intelligence techniques to show trends and patterns in data, which reflects the amount of energy consumption. Different machine learning (ML) based algorithms are there to automatically clean data and format it as well. The algorithm would clean the empty data values, tackle outliers, insert and fill blank values and handle different data stamps. Once all the data is processed sentiment analysis and NLP (natural language processing) algorithms will be applied so that it takes the complex decisions to efficiently optimize the energy. Several research has been developed on energy-related decision-making systems, the study by Liu et al. (2018) and Cui et al. (2017) show a prediction-based detection system with real-time upgradation. Lastly, when all the steps are followed of data collecting, processing, and analyzing, then implementation is done through energy control devices inside the buildings.

There are different research studies present on the efficient usage of energy consumption in buildings. Li et al. (2021) suggested an artificial intelligence-based technique based on reinforcement learning for real-time energy management systems in buildings. Further, the author proposed that this technique can save energy by 26%. The benefit of using reinforcement learning is that the controller continuously learns and improves the model. Although, we can use the pre-trained models for the controllers, and they will eventually learn and adapt to an environment with time. In another study, Hagras et al. (2008) claim that the use of CI will also produce energy-efficient results and adapt to users' conditions. In a study by Chen et al. (2021), the research found an energy-efficient technique for data centers. The proposed technique uses a combo of a rule-based approach and machine learning algorithms to reduce energy usage. The technique shows energy efficiency by 20% if implemented inside the residential building. Another study and research by Dong et al. (2020), shows energy efficiency for commercial buildings. This technique uses an ML-based algorithm to investigate energy consumption and reduce energy consumption. This technique further reduces energy usage by 30%. Another study by Jia et al. (2021) proposed a dual artificial intelligence-based energy efficiency technique, which reduces energy consumption by 28% by using ML techniques along with a rule-based approach. Further, in 2021, research is conducted by Wang et al. (2021) on real-time energy consumption in buildings where smart devices are installed. This study shows the result of 22% less energy consumption by using the deep learning algorithms in the buildings. Another approach by Naug et al. (2019) shows the use of artificial intelligence for developing an energy-efficient consumption model in commercial buildings. This approach shows the collection of data from the controllers and sensors to analyze data for energy-efficient architecture. The proposed architecture was implemented physically, and a case study result was presented to make sure that it provides energy-efficient results in buildings. Another study proposes a new architecture having a real-time energy management system, which has an ANN-based controller and sensors for data collection. This architecture shows real-time energy demands and efficient energy consumption. A case study is provided to show the result having saved and optimized energy consumption results. This architecture was proposed in the study of Megahed et al. (2019). Another approach by Wang et al (2015) is real-time energy management based on MIL (mixed integer linear programming) rolling horizon optimization for buildings in a residential area. The study proposed MOSEK software for solving the problem and minimizing the energy cost considering the RTP policy. A case study is also presented to evaluate the model and result. The proposal shows that it benefits both the owners and operators financially and technically.

**Benefits:**

The reason for using AI-based approaches in energy-efficient systems is that these techniques predict future energy demands by using previous data. These (2017) techniques also take notice of environmental conditions and building characteristics. Previously, energy-efficient systems were mainly introduced to monitor and provide alert facilities. Although, a central system is needed to acquire all the data from these smart buildings, which serves the purpose of energy data analytics. It not only notices the usage of energy but also the peak hours and identifies any device failure or signal issue. A study by Errera et al. (2014) says that smart buildings use a single heat pump at the ground level for several heat pumps joined effectively. With this system, AI can detect the shortage of energy and total energy consumption. At the same time, it can alert and guide the control room on efficiently using energy consumption. Artificial intelligence can be implemented with a variety of sources which includes sensors etc. This allows building controlling management to avoid wasting energy and reduce energy prices. By using the historical data, the machine learning model can predict how much energy is required this year, if the previous year's data is given to the model accurately. Not only year-wise, but the model can provide stats on day-to-day and day-to-night usage energy requirements. This action will further cut energy consumption and costs.

**Data Management:**

To manage data, there are different big data tools available that provide a reusable library of machine learning models that shows a quick way of reusing and adopting DL models. To take maximum advantage of the data, Landgrebe et al. (2021) results show that the related input data should be placed at the same occurrence. If the data is placed correctly, then artificial intelligence-based analytics will provide accurate and easy-to-understand results. The challenge in this type of scenario is to find the related variables when the data is unformatted or unstructured. Peirelinck et al. (2022) study shows that there are different machine learning algorithms available, which can easily classify the unstructured data, which includes sentiment analysis and NLP processes that makes unformatted data into meaningful classified data by taking the variables and description of the data. Dimensionality reduction is also a complex task when it comes to solving a regression or clustering problem of the distinct data. Feature extraction and selection are used to identify and produce key variables to solve the dimensionality reduction problem. This type of solution is efficient when it comes to solving the unsupervised learning problem or having big unstructured data as stated in the study of Chhikara et al. (2022). Training and testing are pre-measured to make any model more effective in a way that it performs the best in all conditions. Different testing environments can be used to test the performance of the model accurately. The study of Chiche et al. (2022) states the different evaluation metrics to be used to test the algorithm of a given problem, for example, accuracy, confusion matrix, F1 score, absolute or mean loss and mean square error, etc. Incremental testing can also be done by taking care of the size of the dataset and the type of the problem solved either supervised or unsupervised.

The paper by Alanne et al. (2022) writes about the machine learning categories, which are divided into supervised, unsupervised, and reinforcement learning. In supervised learning, models are trained on a set of pre-defined variables, which maps the data from the independent to the dependent variable, which is used for the prediction. Sensors are the independent variable when it comes to the building environment. In a classification problem, the model should be trained properly with correct data so that it can predict the future of the dependent variable as stated by Alawadi et al (2020). Unsupervised learning is different from supervised learning as the labels are not available. This type of learning is trained on unlabeled data and learns the data patterns. Both supervised and unsupervised learning have their benefits and cons. Although they are not well suited for adapting, continuously changing environments, and adjustments. This leads to another type of learning, which is reinforcement learning. As stated in Mosavi et al. (2019) reinforcement learning does not have labels like in supervised learning. They have agents, which learn from the environment. The agent makes the changes in the environment and the response gets the reward or punishment. Which reflects whether the provided change is beneficent or not. With time, the agent keeps doing that and learns from the result of reward and punishment. The machine learning model could result in incorrect results if the model is exposed to inconsistencies, then in this case the model should be trained regularly or should be trained when required. A study by Albino et al. (2015) suggested that the building should have both parameters that are identifying the learning gap and self-training of model performance. Similar research provides a database, where the machine learning model learns itself and no manual training is required (Bailey, 2020).

**Security:**

While smart buildings are evolving and attaining new heights of innovation every year. At the same time, it is important to protect the data from theft. This leads to the importance of another important factor which is internet security. Protecting the data of users is an important factor and should not be considered an optional thing as it is the most important thing in developing a smart thing. Data integrity could be compromised if the standards of IoT are not implemented accordingly (Khajenasiri et al. 2017). This will lead to incorrect data collection, which will further result in incorrect decisions of the model, which eventually increase the consumption and cost of the energy. Data collection will also be difficult where buildings are old and built not on modern infrastructure. While hundreds of devices are connected and transfer information to one another, the major challenges are protecting, analyzing, and storing the data. Cho et al. (2020) share insights on data privacy, where data is communicated, shared, activity occurred, or any data movement. Alfafara et al. A survey shows that 90% of people think that data privacy is an important aspect of smart energy-efficient buildings. Another survey states that important aspects of data privacy include data forensics and tracking, mutual trust, and data integrity (Xu et al 2014). Although many improvements are happening in data privacy (Weber, 2010), there is still a need to gradually upgrade the IoT infrastructure.

**Conclusions:**

AI has the potential to revolutionize energy management in buildings, providing a wealth of data-driven insights for researchers and building managers alike. Through machine learning algorithms and AI techniques, we can optimize energy consumption, improve efficiency levels and support sustainability efforts. Real-time monitoring systems boosted by artificial intelligence grant us the opportunity to energize science with innovative strategies that will help green our future - optimizing energy usage within structures while maximizing efficiency at all times.

**Future Works:**

The integration of AI for real-time energy management in buildings promises immense advantages to the global scientific community. By utilizing advanced AI algorithms and machine learning techniques, researchers can process vast amounts of energy data, recognize patterns in consumption rates, and enhance energy efficiency. This evidence-based approach encourages groundbreaking research into sustainable building practices and conservation strategies. Furthermore, with the help of Artificial Intelligence powered systems for monitoring and control, scientists are able to observe environmental conditions more accurately while simultaneously providing invaluable intelligence that could lead to further advances in future studies related to energy optimization.

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**List of abbreviations**

ML – Machine Learning
AL – Artificial Intelligence
NLP - natural language processing
$CO_2$– Carbon Dioxide
RTP - Reappointment, Tenure, and Promotion
ANN - Artificial Neural Network
IoT - Internet of Things

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