Advanced approaches in building energy consumption prediction

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Abstract: Energy consumption prediction in buildings is a major issue in the field of energy efficiency and resource management. In recent decades, the use of Artificial Intelligence (AI) has become an increasingly common approach to improve the accuracy and reliability of these predictions. In this paper, the most used digital technologies such as: AI, Big Data, Internet of Things (IoT), Blockchain, Cloud computing and 5G, which can fundamentally transform the way energy consumption predictions are made in buildings, are presented; the different types of data used in energy consumption prediction are analysed, such as weather data, energy use data and building characteristics; the various AI methods and algorithms are presented, e.g. neural networks, decision trees, support vector and machine learning algorithms, used to improve prediction accuracy. This paper focuses on a conceptual energy prediction model developed for the project "Intelligent system for predicting energy consumption in buildings (PRECONERG)", a project in the first stage of development.

Keywords: Artificial Intelligence, Machine Learning, Prediction Model, Energy Consumption.

Abordări avansate în predicția consumului de energie în clădiri

Rezumat: Predicția consumului de energie în clădiri este o problemă majoră în domeniul eficienței energetice și a managementului resurselor. În ultimele decenii, utilizarea Inteligenței Artificiale (IA) a devenit o abordare din ce în ce mai frecventă pentru a îmbunătăți precizia și fiabilitatea acestor predicții. În această lucrare, sunt prezentate cele mai utilizate tehnologii digitale cum ar fi: IA, Big Data, Internetul Lucrurilor (IoT), Blockchain, Cloud computing și 5G, ce pot transforma fundamental modul în care sunt efectuate predicțiile consumului de energie în clădiri; sunt analizate diferitele tipuri de date utilizate în predicția consumului de energie, precum date meteorologice, date de utilizare a energiei și caracteristici ale clădirii; sunt prezentate diversele metode și algoritmi de IA, de exemplu rețelele neuronale, arborii de decizie, mașinile de vector suport și algoritmi de învățare automată, utilizați pentru a îmbunătăți acuratețea predicțiilor. Această lucrare se concentrează pe un model conceptual de predicție a energiei dezvoltat pentru proiectul „Sistem inteligent de predicție a consumurilor energetice în clădiri (PRECONERG)", un proiect aflat în prima etapă de dezvoltare.

Cuvinte cheie: Inteligență Artificială, Învățare Automată, Model de predicție, Consum de energie.

1. Introduction

In the digital era, technology and innovation have become essential pillars to address the complex challenges of modern society. One of the fields where technological advancements have had a significant impact is that of energy efficiency in buildings. In this context, Artificial Intelligence (AI) has become a powerful tool in managing and predicting energy consumption.

The prediction of energy consumption in buildings has become a priority, given the continuous increase in energy demand and the necessity to manage resources in a sustainable manner.

Energy consumption predictions are essential for efficient resource management and strategic planning of energy infrastructure. They provide valuable information about future energy demand, allowing producers and suppliers to adjust their production and distribution accordingly. These predictions are fundamental in optimizing the use of resources, reducing the risk of overloading the networks, avoiding unnecessary losses and improving energy efficiency.

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These predictions can be used to manage HVAC (heating, ventilation, air conditioning) systems, schedule lighting, optimize the use of equipment and devices, and monitor energy performance. By applying energy consumption predictions to a building, intelligent and more efficient resource management can be achieved, helping to reduce operational costs and environmental impact.

The use of AI brings a new perspective to addressing this challenge, transforming available data into valuable insights and providing personalized solutions for energy efficiency (Rizvi, 2023). One of the key aspects of using AI is its ability to analyse and understand complex patterns in energy consumption data. Machine learning algorithms and neural networks enable the efficient processing of large volumes of information, identifying trends and behaviours that can subsequently be used in accurate predictions (Zahedi et al., 2023).

Another significant contribution of AI in the field of energy efficiency in buildings is its ability to adapt and optimize systems in real-time. Building management systems can benefit from AI to anticipate changes in weather conditions, occupant behaviour, and other variables, thus automatically adjusting the parameters of HVAC systems, lighting, or other energy-consuming devices. In addition to predicting energy consumption, AI can also contribute to the efficient identification and remediation of energy losses in buildings. By analysing data from IoT (Internet of Things) sensors and devices, AI-based algorithms can identify anomalies and provide preventive solutions to reduce energy losses (Martellotta et al., 2022).

The use of Machine Learning (ML) in predicting energy consumption in buildings significantly contributes to energy efficiency. ML is a branch of AI that employs algorithms enabling systems to learn from available data and make predictions or to take decisions without being explicitly programmed for a specific task (Kumar et al., 2023). Integrating an intelligent analysis system with advanced ML capabilities can be valuable in identifying energy-saving opportunities while reducing dependence on human intervention to identify and resolve operational issues (Kawa & Borkowski, 2023). A key advantage of ML-based predictive modelling in building energy consumption management and control applications is that, while classical physical models require detailed information about the target building's properties, ML-based methods are capable of modelling, detecting, and even anticipating energy consumption patterns of a building implicitly by extracting relevant information about the building attributes from historical dates. These methods can generate a variety of features applicable as inputs for ML models (Biessmann, 2023).

Using ML to improve a building's energy efficiency starts with data analysis. ML algorithms constantly incorporate and analyse data obtained from a variety of sources (such as equipment, sensors, and devices) to refine an internal model that can be used to establish evolving trends and identify anomalies. Over time, it will enable an analytics system to learn how a building is performing and detect excess energy use, identify opportunities to save operating expenses and recommend solutions for complex problems. The more data an ML-based analytics system collects on the operation of a set of equipment, the more historical data it will have about how, when and why that equipment is operating, allowing it to make more accurate predictions and better adjustments. When actual energy consumption is higher than predicted, it could indicate inefficiencies (Hamayat et al., 2023).

As the analysis system develops a deeper understanding of the building, advanced algorithms can perform increasingly complex learning processes and use data models to automatically adjust operational benchmarks, initiate actions, and modify building systems and device behaviour (Zahedi et al., 2023). Moreover, ML can also be used for fault detection and prediction. A building's interconnected network of equipment, sensors and devices can generate a large volume of data and trigger multiple alarms when equipment malfunctions. Advanced analysis allows the organization, analysis, and prioritization of this data to produce meaningful insights and isolate vulnerability points and failures. Significantly, ML can surpass traditional fault detection and proactively warn of system and equipment failures before they occur, signalling early deviations. This can be essential for avoiding catastrophic failures, preventing energy wastage, and minimizing downtime.

By integrating ML technologies into energy management solutions in buildings, a significant step is taken towards building a more energy efficient and sustainable environment (Balaji &

Karthik, 2023). The ability to adapt and learn from the available data makes ML a valuable tool in making the use of energy resources more efficient. Thus, the use of AI in the prediction of energy consumption in buildings represents a promising direction for improving energy efficiency and reducing environmental impact. With its capabilities of advanced data analysis and real-time adaptability, AI opens up new opportunities for the development of smart and sustainable buildings, thus helping to build a more energy efficient and ecological future.

While the literature outlines the importance of AI in energy efficiency, this paper highlights its contribution through its comprehensive approach and detailed integration of modern digital technologies and artificial intelligence methods to improve energy consumption predictions in buildings. Unlike studies in the field, which focus more on the general application of AI in energy efficiency, this paper proposes a detailed analysis of specific AI algorithms and methods, as well as associated digital technologies, in the context of energy consumption predictions in buildings. By synthesising these technologies, a more robust and versatile solution for energy consumption prediction is provided, capable of addressing challenges in this domain. Thus, the paper provides a new and detailed insight into how digital and AI technologies can be effectively implemented to improve energy management in buildings and make progress towards a more sustainable and energy efficient future.

The structure of this paper is as follows. In Section 2 are presented the most adopted digital technologies which can transform the way energy consumption predictions are made in buildings. Section 3 presents different types of data used in energy consumption prediction and various AI methods and algorithms. Section 4 discusses about a conceptual energy prediction model. Section 5 includes the conclusions of this paper and future work proposals. The contribution of this paper is to advance the knowledge and understanding in the field of energy efficiency in buildings through the comprehensive integration and evaluation of modern digital technologies and artificial intelligence methods to improve energy consumption predictions.

2. Digital technologies

Digital transformation in the energy sector brings efficiency and accuracy to energy consumption predictions in buildings, integrating technologies such as AI, IoT, Big Data, Blockchain, Cloud computing, and 5G (Figure 1).

Figure 1. Digital technologies in the energy sector

In this new digital paradigm, data analytics platforms, cloud computing, cybersecurity, and device interconnectivity become key elements in the process of optimizing energy efficiency. Digital transformation opens up new opportunities for innovations and solutions towards a more sustainable and intelligent energy future (Weigel & Fischedick, 2019).

2.1. Artificial Intelligence

Artificial Intelligence is one of the increasingly adopted digital technologies in the energy sector (Bedi & Toshniwal, 2019), including in areas such as energy demand forecasting, energy generation and conservation, energy price forecasting, integration of several renewable energies, etc. The widespread application of AI in the energy sector is accelerating the implementation of "the smart buildings", "the smart cities" and "the smart grid" (Behm et al., 2020).

Machine Learning (ML) represents a branch of AI that deals with the development and use of algorithms allowing computer systems to learn from data, identify patterns, and make decisions without being explicitly programmed for each situation. ML is particularly relevant in the field of energy consumption prediction in buildings, as it can contribute to the development of accurate, adaptive, and customized predictive models based on the specificities of each building. These algorithms can constantly adjust the models based on changes in energy consumption and provide more accurate predictions as they collect more data (Benavente-Peces, 2019).

2.2. Big Data

Big Data is an emerging technology with significant potential in the energy sector that involves the collection, storage, and analysis of large amounts of data, providing a clearer perspective on operations and processes in the energy industry (Lyu & Liu, 2021). By collecting and integrating data from IoT sensors and smart measuring devices, Big Data makes a significant contribution to optimizing energy consumption prediction by providing a comprehensive view of influencing factors.

Real-time data analysis is an essential feature of Big Data utilization, which enables the rapid identification of emerging patterns and trends, facilitating immediate adjustments in energy networks management. By implementing ML algorithms, Big Data contributes to the development of advanced prediction models. These models can predict energy demand based on a variety of variables, including weather conditions, user behaviour, and special events, thus ensuring more accurate forecasts. Thus, the use of Big Data in the energy sector has significant potential to improve the efficiency, reliability, and sustainability of the energy industry.

2.3. Internet of Things (IoT)

The Internet of Things (IoT) is defined as an infrastructure that involves physical objects, termed "things", equipped with sensors, software, and other technologies that enable the connection and exchange of data with other devices and systems via the Internet (Rădulescu & Neacșu, 2023).

The nature of "connectivity" makes IoT widely applied in all areas of the energy sector. IoT adoption in the energy sector can reduce downtime, reduce costs and improve profitability, thereby improving energy efficiency. Also, IoT promotes the use of renewable energy sources and reduces the environmental impact generated by energy consumption (Rissman et al., 2020). Furthermore, IoT is increasingly used in smart homes and Internet-connected devices, playing a significant role in the evolution of the energy sector, which is one of the most active domains in the economy. IoT devices can be integrated into buildings to collect real-time data on energy consumption. IoT sensors can monitor temperature, lighting, humidity, and other factors that influence energy consumption (Vučković & Pitić, 2022), contributing to obtaining a comprehensive perspective on energy consumption in the building. This data can then be used to train prediction algorithms.

2.4. Blockchain

Blockchain technology is becoming increasingly present in the energy sector due to its ability to ensure security and transparency in collecting and sharing energy consumption data. It provides a robust platform for managing information related to energy consumption, guaranteeing data integrity and eliminating the risk of manipulation or errors. Thus, blockchain technology represents an essential pillar in the evolution of the energy sector, bringing significant benefits in terms of security, transparency, and efficiency in the prediction and management of energy consumption. However, implementing blockchain in the energy industry also involves technical and security challenges (Vučković & Pitić, 2022).

2.5. Cloud computing

The large volume of data from sensors in building energy infrastructure needs to be efficiently managed, processed and analysed to develop optimal energy management strategies. Cloud computing provides services that allow users to store and share their data on dedicated online platforms. Additionally, these platforms facilitate access to various software programs designed for processing and analysis of the collected data (Mir et al., 2021; Singh et al., 2020).

Cloud computing represents an essential component in the context of energy consumption prediction in buildings, offering scalable resources, improved data accessibility, and computational power necessary for information analysis and processing. The use of cloud computing in the prediction of energy consumption in buildings contributes to operational efficiency, accelerates application development and facilitates access to advanced analytics and ML technologies, ultimately contributing to more efficient management of energy resources.

2.6. 5G

Recent technological advances in the field of communications have had a significant impact on the management of smart energy systems, particularly through the exploration and implementation of 5G technology (Esenogho et al., 2022). In addition to its application at the network level, 5G technology brings benefits to energy management at the micro level, such as in smart buildings (Zhou & Li, 2020), due to extensive and precise data on energy consumption and demand forecast derived from IoT devices and distributed systems that are connected through 5G wireless networks. (Huseien & Shah, 2022). 5G technology can play a key role in the development of advanced solutions for managing and estimating energy consumption in buildings. However, the implementation of these technologies must take into account aspects such as data security, ethical considerations and environmental impact (Petcu & Barbu, 2022).

3. Energy consumption prediction models

For a sustainable future, optimizing energy consumption plays an important role, and AI becomes a powerful ally in this process. Approaches based on AI algorithms provide efficient alternatives for engineering and data mining, and energy consumption data is collected monthly, seasonally and annually for short-, medium- and long-term forecasts.

Data sets from various sources, including smart meters, IoT devices and historical records, feed the AI models used in energy. By training models on historical data, AI systems can accurately forecast future energy requirements, enabling proactive resource management and proactively addressing challenges.

3.1. Data types

For the development of energy consumption prediction models, the following types of relevant data are considered:

- **Weather data**: Weather information such as temperature, humidity, wind speed, and solar radiation is important because it can influence the electricity demand in a building (Meteostat, 2023).
- **Energy usage data:** Hourly, daily or monthly records of electricity consumption are essential for identifying consumption patterns, seasonal fluctuations and trends in energy use. Analysis of these records allows the identification of peak periods, when electricity demand is higher, and periods of lower consumption, such as nights or off-

peak hours. Identifying these patterns makes it easier to plan and adjust systems and equipment to reduce unnecessary electricity consumption (Narayana Palety & Mahalakshmi, 2022).

- **Construction data and building characteristics data:** Information about a building's characteristics, such as age, floor area, thermal insulation, HVAC system efficiency, and lighting type, are used to model its energy consumption. These features also include details of external wall insulation, roof, double-glazed windows, solar protection, ventilation cooling and photovoltaic panels, contributing to a more accurate estimate of the building's energy consumption (Kaggle, 2022).
- **Sensor data:** Data obtained from sensors in a building is a source of information for the optimization and efficient management of energy resources. These sensors monitor a wide range of parameters such as temperature, humidity, air quality, light levels, electricity and heat consumption, as well as presence or movement in different areas. The data is used to optimize the air-conditioning and lighting systems, and to identify areas with potential to improve energy efficiency (Ibarra et al., 2023).
- **Equipment data:** Information about the building's operating schedule influences electricity demand. During peak times, demand increases due to equipment usage, and on days off or holidays, demand may decrease. This information can help to effectively manage energy consumption, optimizing the use of energy resources (Wei et al., 2021).
- **Operating schedule data:** Information regarding the building's operating schedule, including working hours, days off, or holidays, can significantly influence the increase in electricity demand. During peak hours, when building activity is intense, energy demand may increase considerably due to extensive use of equipment and systems such as lighting or computers (Chen et al., 2021).
- **Occupancy data:** The number of people in the building affects electricity demand, increasing energy consumption for lighting and equipment.
  The air conditioning and heating system is influenced by the number of people, requiring more capacity to maintain a comfortable temperature inside. Knowing the schedule and the number of people present in the building allows the effective adjustment of air conditioning and heating settings, contributing to a more rational consumption of electricity and reducing the associated costs (Chen et al., 2021).

There are two general approaches to collecting or generating data used for predicting energy consumption in buildings through data-driven predictive models. The first approach involves *acquiring data* by equipping buildings with technological devices to obtain precise and detailed data or by accessing publicly available datasets (Open Data). The second approach involves using *synthetic data*, which is a dataset developed by a computer, models based on thermodynamic laws, and mathematical calculations.

3.2. Methods and algorithms

Artificial Intelligence has become an essential tool in the prediction of energy consumption in buildings, allowing the development of more accurate and efficient models. Next, we will present the methods and algorithms using AI in the prediction of energy consumption in buildings.

1. **Machine learning methods:**
   - *Supervised Learning*: Algorithms that learn based on labelled examples. This method involves training a model on labelled input and output data, which means that the models are taught to make predictions based on given examples, where both the input data and the corresponding outputs are known. The main purpose of supervised learning is to build a model that can make accurate predictions on new data or in new situations (Sarker, 2021).
   - *Unsupervised Learning*: Algorithms that identify patterns in unlabelled data. This method involves training a model on unlabelled input data. In this case, there are no pairs of associated input and output data, as in supervised learning. The main

goal of unsupervised learning is to discover hidden structures or interesting patterns in the input data (Sarker, 2021).

- *Semi-supervised Learning*: A combination of the two, using both labelled and unlabelled data. This method lies between supervised learning, where all the data is labelled, and unsupervised learning, where there is no information about the data labels. The main purpose of semi-supervised learning is to take advantage of the larger amount of unlabelled data available to improve the performance of the learned model (Sarker, 2021).

- *Reinforcement Learning*: A branch of AI in which an agent (the learning system) learns to make decisions in a specific environment in order to maximize a long-term reward. This is a learning process based on the agent's continuous interaction with the environment, learning from experience and experimentation (Sarker, 2021).

2. **Machine learning algorithms:**

- *Support Vector Machines (SVM)*: is a next-generation learning method used for regression or classification. This identifies a hyperplane that maximizes the edge between different classes. This hyperplane serves as a decision boundary, allowing SVM to be used effectively in classification and regression problems, especially where the data are non-linear or high-dimensional (Chopra & Khurana, 2023).
- *K-means Clustering*: is a method of analysing data and grouping (clustering) it into distinct sets or clusters. The main purpose of the K-means algorithm is to partition the data into K sets, where each set represents a cluster (Nie et al., 2023).
  In the context of energy consumption prediction, K-means Clustering proves essential for understanding and managing the voluminous and complex data associated with this field. By applying the K-means algorithm to historical energy consumption data sets, it is possible to identify significant consumption patterns and segments. This segmentation allows for a more detailed analysis of consumer behaviour as well as the factors that influence energy demand in different contexts and time periods. Thus, K-means Clustering serves as a fundamental tool in the development and implementation of advanced energy prediction.
- *Decision trees:* are a powerful and flexible method to make predictions of energy consumption in buildings. They enable the analysis of historical data and the identification of key factors that influence energy consumption, such as temperature, humidity, occupant activities and characteristics of the building itself. By modelling these complex relationships, decision trees provide a deep understanding of energy consumption behaviour and can help identify optimal energy efficiency strategies. They are also useful for making accurate predictions of energy consumption in buildings, thus facilitating efficient resource planning and optimization of energy costs. Using decision trees, building owners and energy managers can make informed and strategic decisions to improve energy performance and reduce environmental impact. Using decision trees, informed and strategic decisions can be made to improve energy performance and reduce environmental impact (Ramos et al., 2022).
- *Random Forest*: is a technique that relies on multiple decision trees to improve model performance: each tree is trained on a subset of data (obtained by random sampling) with a random selection of features (attributes), and at the time of prediction, Random Forest combines the predictions of all the trees to obtain a final prediction (Jayaraman et al., 2023). Random Forest is successfully used to make energy consumption predictions, especially when working with complex datasets containing multiple features and seasonal variations (Dudek, 2022).
- *Gradient Boosting (GB)*: is an efficient and powerful method in energy consumption prediction. By analysing historical data and relevant characteristics such as temperature, humidity, and more, Gradient Boosting algorithms can

identify patterns and trends in energy consumption. These models can be used to make accurate predictions about energy demand in different contexts and conditions (Lu & Mazumder, 2020). Gradient Boosting can also help optimise energy efficiency in buildings and energy systems by providing valuable information about consumer behaviour and factors influencing energy consumption.

- *Gradient boosting decision trees (GBDT)*: it represents a prediction model composed of Gradient Boosting model and decision trees used in different fields. The GBDT model shows the best performance in predicting the energy consumption of appliances in a low-energy house. GBDT is also called Multiple Additive Regression Trees (MART) or Gradient Boosting Machine (GBM) and is an iterative decision tree (Wang et al., 2020).
- *Regression Trees (RF)*: They are representative of a predictive integration model comprising multiple regression trees that are used to train and make predictions on samples. It can automatically perform feature selection to determine the interaction between different variables and still maintain high prediction accuracy in the case of missing features (Seyedzadeh et al., 2019).
- *Extreme Gradient Boosting (XGB)*: It can handle non-linear relationships well without considerable adjustments, and is a gradient-boosting decision tree designed for speed and performance (Kamel et al., 2020).

3. Methods based on neural networks:

- *Feedforward Neural Networks (FNN):* These networks can capture the intricate connections between input variables (such as temperature, time, day of the week, special events, etc.) and energy consumption (Wang et al., 2023).
- *Recurrent Neural Networks (RNN)*: These networks are useful for time series data, having the ability to remember previous information. Due to their ability to capture sequential dependencies in data, RNNs are effectively used for time series modelling and prediction of electricity consumption (Zagrebina et al., 2019).
- *Long Short-Term Memory (LSTM) Neural Network*: Suitable for energy consumption prediction models that enables the identification and efficient use of significant relationships between historical data, thus contributing to a better understanding of energy consumption behaviour. The integration of these networks in predictive models brings a significant contribution to the accuracy of the estimates, making them essential tools in the optimization of power grid operations and in the efficient management of energy resources (Alexandru et al., 2023).
- *Convolutional Neural Networks (CNN):* Associated with image processing, but can also be adapted to address time series problems, such as predicting energy consumption at different locations. To improve performance in energy consumption prediction, hybrid architectures can be created that combine CNNs with other types of neural networks, such as recurrent neural networks (RNNs) or LSTMs, to capture both time series features and temporal dependencies (Chen, 2023; Alexandru & Pupăză, 2020).
- *Auto-encoding:* As energy data is varied and complex, a special type of artificial neural networks is sometimes needed to reduce the dimensionality of the data, to extract meaningful features from this data, or to generate new data. For these processes, auto-encoders networks are used. Autoencoders are neural networks that learn to compress and process their input data. After processing, features are extracted from the input data that are more relevant and allow for an easier solution to the ML problem (Shah & Ganatra, 2022).

4. Conceptual model

In an era where energy efficiency and sustainability concerns are becoming increasingly pressing, the development of an intelligent system for predicting energy consumption in buildings is an imperative necessity.

The project "Intelligent system for predicting energy consumption in buildings (PRECONERG)" is an ongoing project that is currently in its first stage of development. The project aims to develop, test and validate an energy consumption prediction system using advanced prediction techniques with the help of energy consumption prediction models based on AI. The system will contain smart devices for collecting energy parameters, environmental sensors and a cloud platform for data storage and aggregation, including an interface for presenting the obtained results. It will integrate advanced ML capabilities to identify energy saving opportunities while reducing reliance on human intervention to identify and resolve operational issues.

This article proposes an analysis of a conceptual model that serves as a foundation for such a system, offering a systemic and integrated perspective on estimating energy consumption in office buildings. The proposed conceptual model for the intelligent system for predicting energy consumption in office buildings is built on systemic principles and emerging technologies such as artificial intelligence and data analysis. It aims to integrate key elements of the built environment and energy consumption, providing a robust platform for estimating and optimising energy use in office buildings.

A conceptual model for predicting energy consumption is presented in Figure 2.

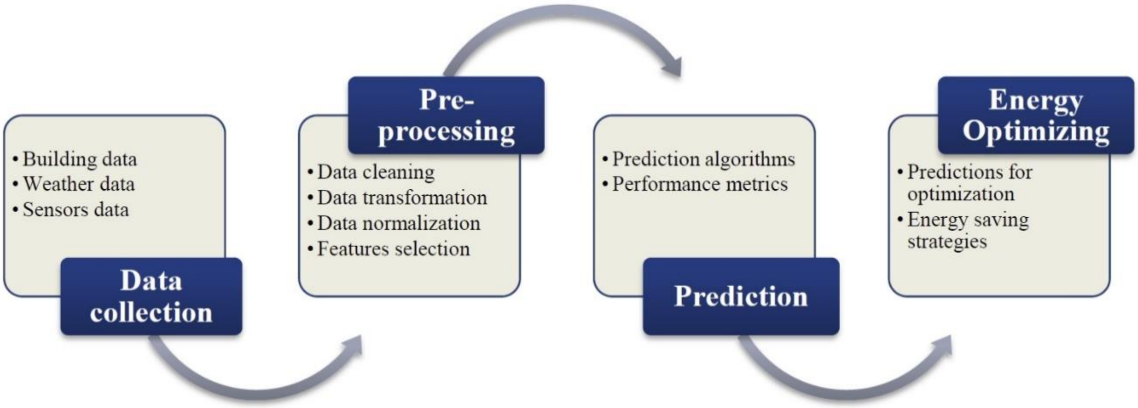

Figure 2. Conceptual model for energy consumption prediction

Energy consumption in buildings can be influenced by a variety of factors, which can be categorised into three main groups: building characteristics, occupant behaviour, and external environmental factors. The connection between these factors is complex and interrelated. For example, building characteristics such as the quality of insulation and the materials used in the building envelope (walls, roofs, windows) and HVAC efficiency directly impact energy consumption, but occupant behaviour, such as thermostat settings and lighting usage, can also significantly influence energy usage patterns. Additionally, external environmental factors such as climate and seasonal variations interact with both building characteristics and occupant behaviour to further impact energy consumption.

A proposed methodology for building and evaluating an energy consumption prediction model is presented below:

Data collection: Data on building characteristics (floor area, installation type, year of building construction, etc.), meteorological data collected by on-site sensors (annual average temperature, annual temperature, total annual precipitation, starting rating of energy consumption, etc.) and daily or hourly measurements of the building's energy consumption are collected over a certain period of time.

Pre-processing: Data is prepared by cleaning, transforming and processing it, making it suitable for predictive models, while improving the accuracy and efficiency of predictive models. Data pre-processing includes data integration, missing value processing, outlier assessment and processing, data standardisation, and important feature selection. As the data comes from various sources, it is necessary to standardise it to ensure the cohesion and integrity of the information. Data cannot be used in analysis and modelling without being normalized, and adjusted/transformed. Data normalisation is an important step in removing disproportion between data that can vary significantly in scale and amplitude.

Prediction: This involves the use of different ML algorithms as well as the tuning of hyperparameters to obtain performing models. Among the ML algorithms presented, we intend to use the following algorithms: Random Forest, Decision Tree, Support Vector Machine, and Gradient Boosting Decision Tree. For data with complex temporal characteristics, we will use methods based on neural networks such as Recurrent Neural Networks and Long Short-Term Memory Neural Networks. The prediction process is composed of:

- *Model training and testing:* The data set is divided into a training set and a test set. The training set will be used to build the model, which will contain the available features (e.g., temperature, day of the week) to make predictions on electricity consumption, while the test set will be used to evaluate the model's performance, using metrics such as Mean Squared Error (MSE) or Mean Absolute Error (MAE).
- *Validation and evaluation:* The model will be validated on a validation set to observe the performance of the predictions applied to unknown data.

After validating and evaluating the model, it can be used to make predictions for energy consumption based on current data or weather forecast. One can then tune the model by tuning the hyperparameters, such as learning rate or number of layers in a neural network or the number of trees in a random forest to improve its performance or to cope with changes in the data. It is important to consider multiple types of variables and perform detailed analysis to develop an accurate and efficient model.

The following software tools are intended to be used for solving these tasks: as a programming language, we will use Python with its extensive libraries and frameworks in machine learning, such as TensorFlow, Keras, Scikit-Learn, and PyTorch for building and training models, Pandas and NumPy for data manipulation and analysis, and Matplotlib for visualising data and model performance. By integrating these tools, the prediction model will be effectively developed, validated, and optimised to ensure high accuracy and reliability in forecasting electricity consumption.

Energy Optimization: After the model is properly evaluated and adjusted, it can be used to make future predictions. These predictions can then be processed and used to make operational decisions regarding energy consumption. By implementing effective energy optimisation strategies, one can maximise the use of available resources and reduce unnecessary energy losses.

To optimise energy consumption in the conceptual prediction energy model, effective methods include utilising predictive analytics for forecasting, implementing real-time optimisation algorithms, integrating demand response strategies, deploying energy management systems, optimising control algorithms for HVAC and lighting systems, integrating renewable energy sources, employing continuous monitoring for performance optimisation, and engaging occupants through education and feedback mechanisms.

Thus, the conceptual model proposed for the intelligent system for predicting energy consumption in buildings represents a solid basis for the development of innovative and efficient solutions in the field of energy efficiency. By integrating advanced technologies and a systematic approach, it can significantly contribute to increasing the sustainability and energy performance of buildings, in line with global goals to combat climate change and reduce energy consumption.

5. Conclusions

The prediction of energy consumption in buildings represents a major challenge in the field of energy efficiency and resource management.

Digital technologies such as AI, Big Data, IoT and Blockchain have revolutionised the approach to this problem, increasing the accuracy of predictions and opening new perspectives for the development of smart and sustainable buildings.

Analysing various types of data, implementing advanced AI algorithms and introducing intelligent prediction systems are essential steps towards creating an energy efficient and sustainable building.

The presented conceptual model demonstrates the potential of digital technologies to transform the way energy consumption in buildings is managed and provides concrete insight into the implementation of these technologies in a real-world context.

Although the project is still in the early stages of development, it highlights the significant potential of advanced approaches in improving energy efficiency and resource management in buildings. Integrating intelligent energy consumption prediction systems and applying energy efficiency strategies can optimise the use of available resources and reduce energy losses.

However, limitations and challenges are also associated. Prediction systems can be influenced by variations in weather conditions or changes in user behaviour, which can lead to errors in energy consumption estimates. In addition, the costs and difficulties of implementation may be obstacles for certain buildings or owners. In the future, it is essential to find innovative solutions to overcome these challenges, including the development of more robust algorithms, tighter data integration, and reducing the costs associated with implementing predictive systems.

In future work, predictive models will be developed to make more accurate predictions based on real building energy consumption data.

In conclusion, the smart use of digital technologies and AI opens up new horizons in energy efficiency and resource management in buildings.

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