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Energy Management in Modern Buildings Based on Demand Prediction and Machine Learning—A Review

Seyed Morteza Moghimi *, Thomas Aaron Gulliver and Ilamparithi Thirumai Chelvan

Department of Electrical and Computer Engineering, University of Victoria, P.O. Box 1700, STN CSC, Victoria, BC V8W 2Y2, Canada; agullive@ece.uvic.ca (T.A.G.)
* Correspondence: seyedmortezamoghimi@uvic.ca

Abstract: Increasing building energy consumption has led to environmental and economic issues. Energy demand prediction (DP) aims to reduce energy use. Machine learning (ML) methods have been used to improve building energy consumption, but not all have performed well in terms of accuracy and efficiency. In this paper, these methods are examined and evaluated for modern building (MB) DP.

Keywords: demand response; energy flexibility; green buildings; machine learning; optimization; smart buildings

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1. Introduction

The design and construction of residential and commercial buildings are among the most energy-intensive activities worldwide. Buildings contribute 20% to 40% of total energy usage [1]. According to the European Union (EU) [2], urban buildings are responsible for 40% of global energy consumption and 33% of greenhouse gas (GHG) emissions. Consequently, governments are motivated to address increasing energy consumption by reducing emissions and improving energy efficiency while ensuring the comfort of building residents [3]. To reduce energy consumption, the European Commission (EC) has proposed nearly zero-energy buildings (NZEBs) for 2030 [3].

Figure 1 illustrates the significance of energy reduction in terms of CO_2 emissions and cost based on data from home energy calculators (HECs) [4]. The figure gives the results of comprehensive questionnaires administered by a United Kingdom (UK) university. Study participants were randomly assigned one of three versions of the HEC which presented energy consumption in kilowatt hours. Responses were thematically coded by two independent reviewers, leading to five distinct classes: energy-related, cost, environmental, a combination of cost and environmental, and 'not worth it', indicating a lack of incentive to reduce energy use, among others.

Strategies for demand prediction (DP) [5] are among the solutions recommended by the EC to reduce energy consumption [6,7]. These strategies include price-based demand response (DR), incentive-based DR, time-based DR, automated DR, and capacity-based DR. However, DP has implementation challenges such as operational and technological limitations, as well as data availability and accuracy issues [8]. Machine learning (ML) methods to address these challenges have been proposed [8,9]. In modern energy management, optimization techniques are often employed to reduce energy consumption and/or cost. This paper examines ML methods considering their deployment, accuracy, cost, and efficiency for modern buildings (MBs), e.g. smart and green buildings (SGBs).

The remainder of this paper is structured as follows. Section 2 presents current ML methods and their applications. Section 3 provides a review of ML techniques for predicting building energy and the related datasets. Finally, Section 4 provides some concluding remarks.

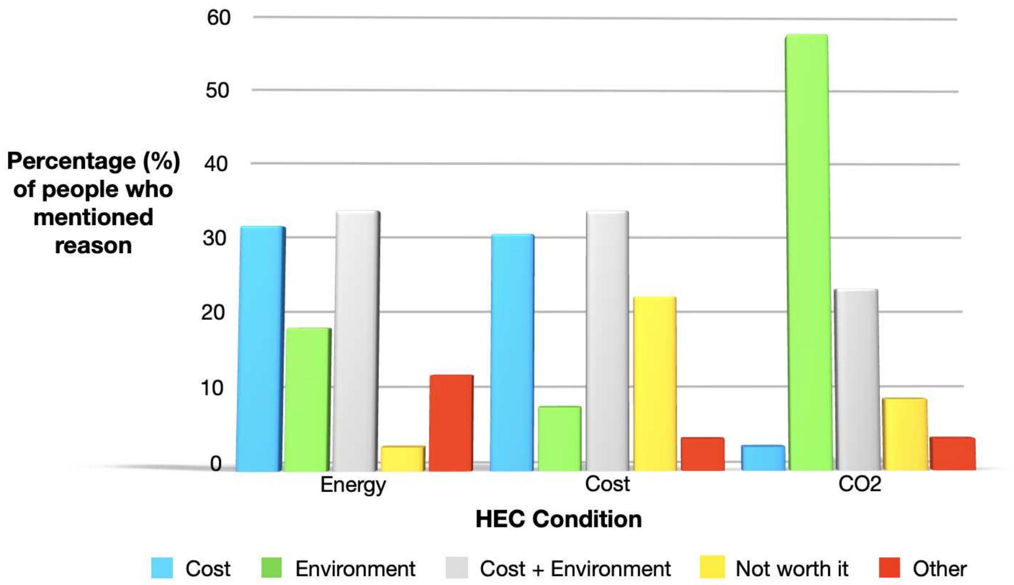

Figure 1. Reasons why reducing energy consumption is important [4].

2. ML Methods

Figure 2 illustrates the ML process, which includes data collection, feature extraction, training, evaluation, and prediction [10–12]. ML methods have been designed for diverse tasks such as data analysis and pattern recognition.

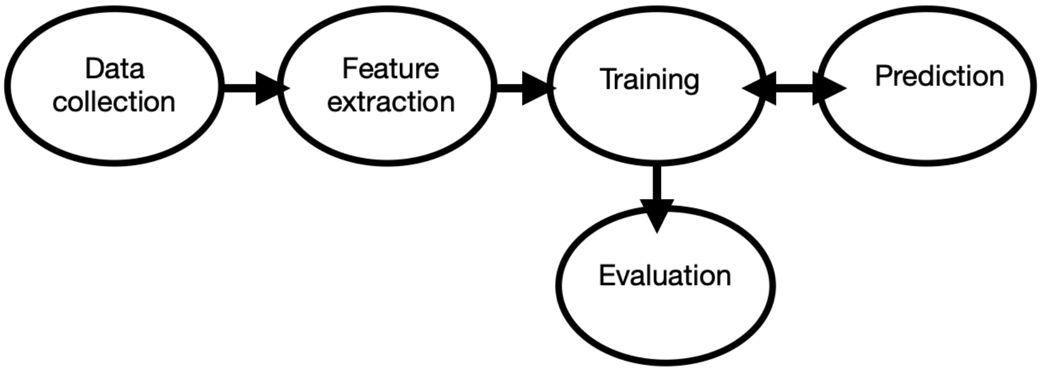

Figure 2. The machine learning (ML) process.

ML methods can be categorized into three primary groups: supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL) [10,11]. Semi-supervised learning combines aspects of both SL and UL. ML methods can also be classified as categorical or continuous. Continuous methods include algorithms such as singular value decomposition (SVD), principal component analysis (PCA), K-means, random forest (RF), regression (linear and polynomial), and decision trees (DTs). Categorical methods are used in RL algorithms for tasks such as robot navigation and gaming. UL methods commonly employ hidden Markov models, clustering, and association analysis. Clustering methods often involve SVD, PCA, and K-means. Neural networks (NN) are employed in SL and UL for tasks such as regression, classification, sequence-to-sequence tasks, clustering, and dimensionality reduction. The selection of an NN architecture depends on the specific problem and the available data [10,11]. Figure 3 illustrates the variety of ML algorithms.

2.1. Supervised Learning (SL)

SL employs feedback for prediction by learning the map from input to output [10,11]. SL algorithms can be categorized as follows.

2.1.1. Regression Algorithms

Regression algorithms are used to predict advertising popularity, estimate life expectancy, forecast markets, predict population growth, and forecast weather. Issues with these algorithms include overfitting, underfitting, multicollinearity, heteroscedasticity, outliers, missing data, non-linearity, autocorrelation, data scaling, and data transformation. These issues can be addressed through data preprocessing, feature engineering, model selection, and regularization [13–15].

2.1.2. Classification Algorithms

Classification algorithms are used to determine a mapping based on the input to classify or categorize the output. Classification algorithms include linear regression (LR), ridge regression (RR), NN regression (NNR), least absolute shrinkage and selection operator (LASSO), DT regression (DTR), RF, K-nearest neighbors (KNNs), and support vector machines (SVMs) [13–15].

2.2. Unsupervised Learning (UL)

UL leverages the inherent structure within a dataset for categorization. The goal is to partition the data based on similar traits [16]. NNs are frequently used in UL as they can uncover patterns or structures within unlabeled data. UL applications include clustering, dimensionality reduction, feature learning and extraction, anomaly detection, generative modeling, and density estimation [15,16].

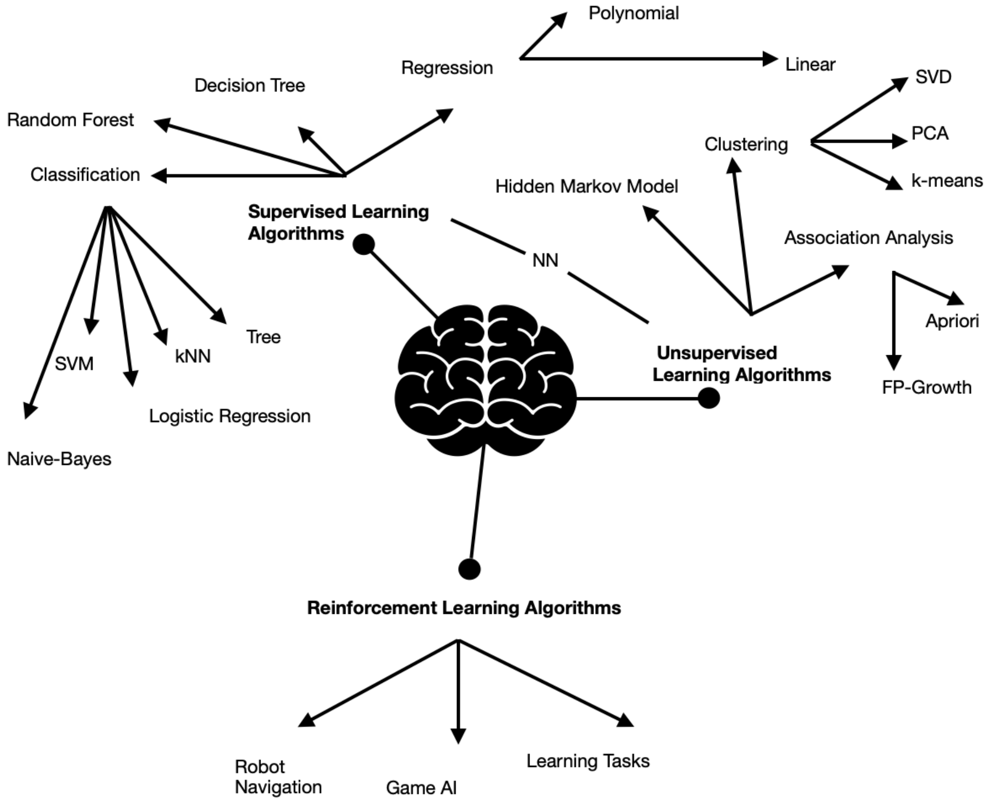

Figure 3. Machine learning (ML) algorithms [16,17].

2.3. Reinforcement Learning (RL)

RL is used to solve problems by maximizing anticipated rewards. It often employs a Markov decision process (MDP) which has states, strategies, actions, and functions. RL reinforces important rules while diminishing the effecst of others [17].

In summary, clustering concentrates on data point grouping, classification assigns data to classes, regression predicts continuous values, UL uncovers patterns without labels, and SL trains models based on labeled data for prediction. The use of ML methods in applications such as MBs [18] can be categorized as single, hybrid, or ensemble methods [19]. For performance evaluation, metrics such as mean squared error (MSE), mean absolute error (MAE), accuracy, and precision are often employed.

2.4. Single ML Methods

In this case, a single method such as SVD is employed. Recurrent NN (RNN) and back propagation (BP) artificial NN (ANN) methods were employed in [20]. These single ML methods were used to compare DP results with official data on electricity consumption in Turkey. An adaptive neuro-fuzzy inference system (ANFIS) was used in [21] for a case study in Ontario, Canada. The thirty years of data available in [20] were used with the proposed model for electricity and energy DP.

2.5. Hybrid ML Methods

Hybrid ML methods combine two or more approaches to enhance performance [22]. This can improve accuracy and provide flexibility in handling complex tasks. Particle swarm optimization (PSO) and a genetic algorithm (GA) were employed in [23] for electricity DP within India. A hybrid model that incorporates wavelet decomposition (WD) and support vector regression (SVR) was used for hourly electricity prediction in [24] using data collected from hotels and malls.

Hybrid ML methods can also adapt to different data types and problem domains by leveraging the strengths of the methods. However, the scalability and feasibility of hybrid methods in real-world applications can be a concern due to factors such as computational complexity, data volume, and data quality. Thus, the decision to employ single or hybrid ML methods should consider the problem, data, resources, and objectives.

2.6. Ensemble ML Methods

Ensemble ML methods involve multiple classifiers and can be sequential or parallel. Given the constraints of hybrid and single methods such as data collection and model design, ensemble prediction methods have been developed such as the approach in [25]. An ensemble method which employs regression for electricity DP in the USA was proposed in [26]. Results were obtained using a small number of building datasets. The ensemble bagging trees (EBTs) method was introduced in [27] to provide improved building energy prediction performance compared to the classification and regression tree (CART) method.

A comparison between ML and regression-based methods is now given.

2.7. Comparison of ML and Regression-Based Methods

Regression is extensively employed in ML models. It is frequently used to estimate the relationship between load and other variables by predicting the correlation between a variable or predictor and an object [28]. When considering model selection and regularization techniques for an application, it is important to consider methods that align with the data characteristics and analysis. The choices for several application areas are given below [13,14,29].

2.7.1. Economics and Finance

Model: Depending on the complexity of the relationships between economic indicators, LR or more advanced techniques such as polynomial regression (PR), RR, or LASSO regression can be employed.

Regularization: LASSO can be advantageous for better generalization and handling multicollinearity.

2.7.2. Natural Language Processing (NLP)

Model: Techniques such as logistic regression are often used for sentiment analysis and text classification. Language modeling typically employs methods such as RNNs or transformer-based models.

Regularization: Techniques such as dropout are beneficial to prevent overfitting in NNs.

2.7.3. Image and Signal Processing

Model: Convolutional NNs (CNNs) are often used for image denoising, deblurring, and super-resolution tasks.

Regularization: Techniques such as weight decay and batch normalization are commonly used to regularize CNNs in image processing.

2.7.4. Energy and Power Systems

Model: Depending on the complexity, LR or more sophisticated methods such as autoregressive integrated moving average (ARIMA) can be used for power grid load forecasting.

Regularization: LASSO or RR can be used to overcome multicollinearity and overfitting in energy consumption prediction models.

2.7.5. Transportation and Traffic Engineering

Model: LR, time series analysis, or autoregressive models are suitable for traffic flow prediction and transportation demand modeling.

Regularization: RR has been used to improve robustness and prediction accuracy in traffic-related models.

The suitability of methods and techniques can also depend on dataset size, noise, and other factors unique to the application. Regression methods are also used to model time series data and explore causal links between variables. Thus, they are employed in many engineering applications [13,14,29].

Statistical methods, known as regression analysis, have been employed to uncover relationships between variables. The methods used in regression analysis for ML include LR, logistic regression, PR, softmax regression (SR), RR, LASSO, and elastic net regression (ENR). Prediction is essential in establishing relationships between dependent and independent variables [13,14,29]. In [29], both ANNs and hedonic pricing were used with real residential property data to estimate market prices.

As previously mentioned, the primary regression methods are simple LR, multiple LR, PR, SVM, DTR, and RF. Each method has advantages and disadvantages which should be considered in selecting the most appropriate method for a given application.

2.8. Classification and Regression Methods in ML

Classification involves identifying or seeking a model or function to divide data into different categories. Classification and regression methods are commonly employed to solve prediction problems. Regression is often used with continuous data, as indicated in Table 1 [29].

Various methods have been considered for DP including multiple regression, exponential smoothing, iterative re-weighted least-squares, autoregressive moving average (ARMA), ARIMA, adaptive load forecasting, AR stochastic time series, SVM, GA, FL, and NN. A comparison of regression and ML methods for DP was presented in [30]. Gaps in existing research and some research challenges were given in [31]. The performance of supervised ML models including KNN, LR, and RF was considered in [32] for hourly DP using an electricity dataset from Sydney, Australia. It was shown that KNN provides the best performance.

Understanding the merits and drawbacks of regression and classification, and the associated methods and algorithms, is essential to achieving satisfactory DP performance. In [13,14,29], it was demonstrated that soft-computing-based DP strategies can yield substantial performance benefits. Furthermore, hybrid methods have gained popularity due to their improved precision and efficiency in solving prediction tasks [13,14,29]. These results indicate that ML methods have had a pivotal role in shaping DP strategies.

Table 1. Comparison of classification and regression methods [13,14,29].

Factor	**Classification**	**Regression**
Mapping	Predefined categories	No predified categories
Values	Discrete	Continuous
Predicted data type	Unordered	Ordered
Metric	Accuracy	RMSE
Sample algorithms	DT, linear programming, NN, statistics	RT, simple and multiple regression analysis, LR, nonlinear regression analysis

3. Literature Review

3.1. ML Methods for DP

In the past three decades, ML methods have received significant research attention across a diverse range of applications [33]. This section examines the use of these methods for DP.

Wang et al. [27] used the EBT algorithm for energy DP in buildings on the University of Florida campus with the goal of reducing energy consumption. Chen et al. [24] employed SVR and multi-resolution wavelet decomposition (MWD) for DP of hourly electricity consumption considering data from hotels and malls and the non-stationary operated building (NSOB) problem for a 24-hour cycle. Li et al. [34] used K-means with a spatiotemporal structure for travel within Shenzhen, China, to investigate transportation demand. Zhou et al. [35] integrated multi-output SVM (MSVM) and multi-task learning (MTL) for traffic DP in Taipei, Taiwan. Chouikhi et al. [36] leveraged a PSO algorithm based on an effective learning process [37] to tune an echo state network (ESN) for time series prediction. Amasyali et al. [31] employed ML algorithms such as SVM and ANN for energy consumption DP within several types of buildings.

Buddhahai et al. [38] introduced a multi-purpose classification system with a new learning structure using K-means clustering for high-power load monitoring. DP and load behavior were analyzed to optimize power consumption performance. Ahmadzadeh et al. [39] investigated the application of ML and deep learning (DL) algorithms to distributed smart grids (SGs) considering security and reliability [40]. The KNN, naïve Bayes, and DT methods were shown to improve offloading decision accuracy and thus energy efficiency.

ML methods have been employed for energy management in malls and hotels [24], energy reduction in buildings [27], heating and cooling demand management in buildings [28], property market price analysis [29], building energy consumption analysis [31], power load analysis [33], urban traffic control [34], time series prediction [36], antenna design prediction [38], adaptive authentication for wireless networks [41], distributed SG performance enhancement [39], energy efficiency [40], and load maintenance and peak shaving in buildings [42].

3.2. ML-Based Prediction Methods

Figure 4 shows that ML algorithms for DP in buildings can be categorized into engineering-based, AI-based, hybrid, and data-driven methods. Engineering-based methods employ thermodynamic principles to model and analyze energy demand, while data-driven methods draw insights from the available data [31]. Moreover, ML-based prediction methods have been proposed to improve performance and efficiency.

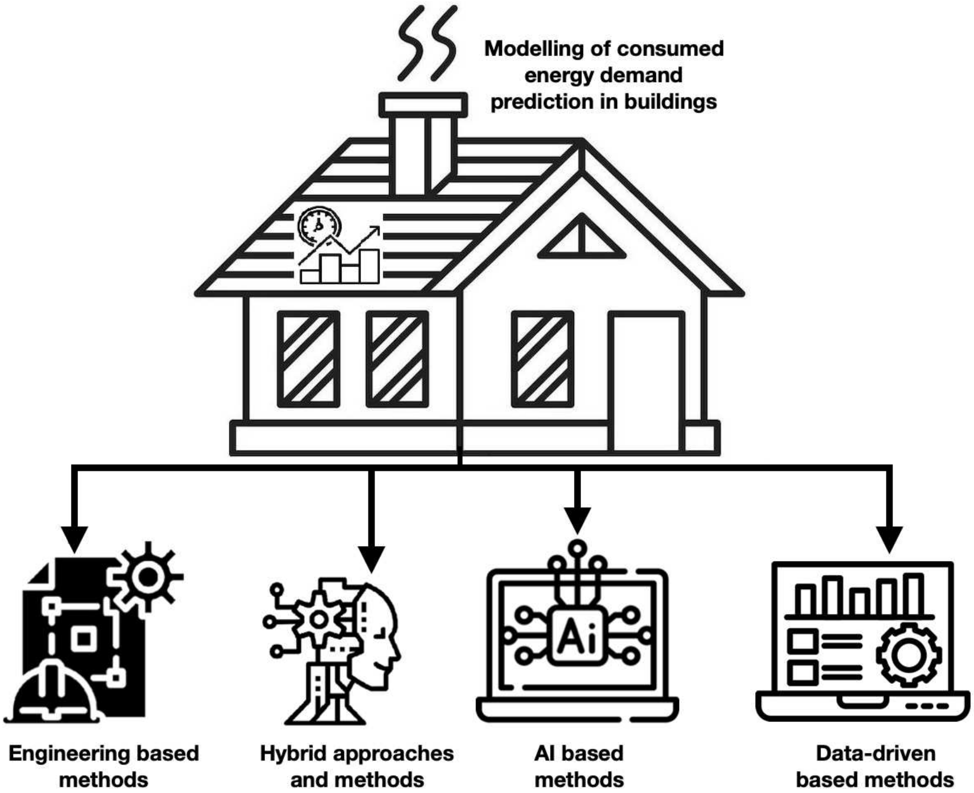

Figure 4. Building energy consumption demand prediction (DP) categories [31].

Johannesen et al. [32] considered ML-based prediction methods including KNN, linear, and RF regression for electricity network load demands. Al Mamun et al. [43] employed DP within power systems for robust load management, including fault prediction. The results obtained illustrate the advantages of hybrid methods. Queen et al. [44] developed an ML model for prediction within IEEE 14 and 30 bus networks. LR and PR models were employed to forecast costs and stabilize voltage in an investigation of the interplay between technology and economics in renewable energy systems (RESs).

Zhang et al. [45] introduced a self-adaptive and hierarchical methodology for real-time voltage stabilization. A hierarchical power system model was developed that incorporates discrete learning. Luque et al. [46] used historical data and economic factors to anticipate demand in a Spanish electrical network. The power consumption behavior of 27 million users was examined using regression, variance analysis, and categorization based on spatial and cost considerations specific to Spain. The results were used to guide decision making for electricity retailers in the power market. Ahmad et al. [47] examined ML and data mining methods for DP, including ANN, SVM, clustering, and statistical-based methods for energy mapping, profiling, and prediction. The four approaches to energy DP, namely engineering-based, AI-based, hybrid, and data-driven, as shown in Figure 4, were considered [31].

3.3. Validation in DP

Management of energy consumption within micro-grids (MGs) plays a pivotal role in the evolution of SGs and smart buildings (SBs). Real-time prediction and load scheduling are critical to leveraging the tradeoff between energy demand and cost. This requires validation to substantiate results and corroborate assertions. For example, Queen et al. [44] used cross-validation (CV) to select a suitable model. Godinho et al. [9] used MAE and root MSE (RMSE) for model evaluation, while Shahriar et al. [48] employed K-fold CV for electric vehicle (EV) charging prediction. Khan et al. [49] conducted dataset testing and model validation to evaluate ML models' accuracy. Sajjad et al. [50] proposed a hybrid ML-based energy DP model that combines CNNs with gated recurrent units (GRUs). Testing and validation within a two-tiered structure were conducted to ensure accurate electricity consumption prediction.

3.4. MB Features

Smart and environmentally conscious MBs are being designed to provide a variety of features catering to both building owners and inhabitants. The focus is on sustainable buildings (SUBs) [51,52] that incorporate elements such as intelligent, automated, and adaptable management systems, indoor climate regulation, and energy-efficient measures. However, the promise of SBs has yet to be realized [53].

Market adoption in the context of SBs was explored in [54]. It was argued that this depends on how users perceive the benefits. For example, enhanced energy management can result in diminished control over building operations. MBs share many features with SBs including advanced HVAC systems, sophisticated information processing capabilities, and comprehensive building management systems (BMS) [55].

3.5. MB Components

MBs employ components from advanced HVAC systems to responsive BMSs. They play a vital role in realizing the vision of a sustainable and intelligent future. These components are discussed below.

3.5.1. Building Heating and Cooling Systems

The solutions proposed in [56] not only contribute to improvements in building electrical systems and their components, but also facilitate user energy savings, particularly when coupled with RESs [57]. Furthermore, the adoption of effective policies and solutions [58] plays a crucial role in stabilizing and reducing GHG emissions. The energy performance assessment of buildings conducted by the EC [59] from 2010 to 2018 illustrates the steps being taken [60] and the tradeoffs between economic growth, urban building energy consumption, and economic outcomes.

A significant percentage of building heating and cooling systems have suboptimal efficiency. It was shown in [61] that over 80% of GHG emissions are from such systems. This necessitates examining the energy demands associated with HVAC systems, as well as the heating and lighting requirements [61,62]. Thermostatically controlled loads (TCLs) including air conditioners, hot water storage tanks [63], and water heaters have emerged as promising and adaptable resources to meet energy demands. TCLs are flexible loads (FLs) that can be used to reduce the effects of power consumption fluctuations on thermal generators [64].

Technologies such as traditional and pulsating heat pipes have been shown to improve the energy efficiency of HVAC systems [65] via efficient heat exchange [66]. Pulsating heat pipes provide high thermal conductivity and can rapidly and efficiently cool building components [65,67]. Heat pipes are an important component of building heating and cooling systems to improve energy conservation and reduce GHG emissions.

3.5.2. Component Integration with SGB Technologies

Figure 5 illustrates the SGB concept, which includes sustainable site practices, water-efficiency measures, energy and atmospheric considerations, material and resource strategies, indoor environment quality enhancements, and innovative design processes. The SB concept includes the Voice over Internet Protocol (VoIP), data networks, video-distribution mechanisms, wireless systems, robust cabling infrastructure, HVAC control systems, power management solutions, programmable elements, lighting controls, and comprehensive facility management. The shared traits are energy optimization, enhanced performance, supplementary commissioning, precise measurement and verification, carbon dioxide monitoring, adaptable system control, and continuous monitoring. They allow SGBs to attain energy savings, reduce their environmental impact, and provide healthier and more comfortable living and working environments for occupants.

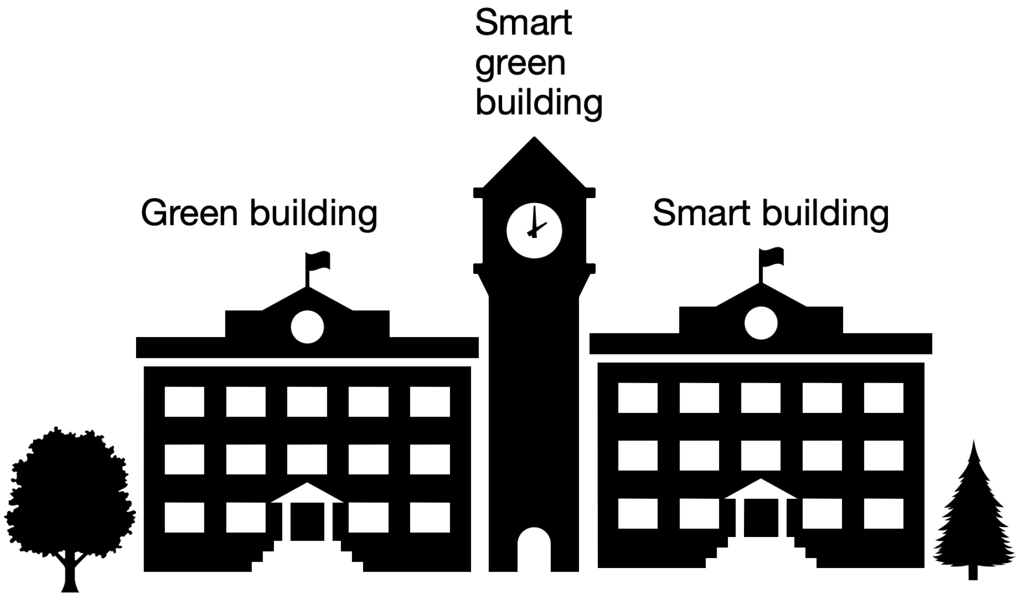

Figure 5. Smart green building (SGB) characteristics [17].

FLs can be used to mitigate the challenges associated with DR. They allow power consumption management within designated time intervals [63,64]. Moreover, TCLs can be used to reduce energy consumption during peak periods. This is important as electricity consumption within MBs is projected to outpace the growth in energy generation, thereby increasing the discrepancy between supply and demand [68]. To address this problem, RESs and MGs have emerged as solutions to improve local reliability, energy management [69], and network efficiency [70]. Amir et al. [71] examined the integration of SBs and GBs. SBs were shown to be well suited to improving energy efficiency in [70]. The International Data Corporation (IDC) has reported an increase in the number of SBs from 6.3 billion in 2014 to 17.4 billion in 2019 [71]. System automation and control in SBs can lower life-cycle expenses [72,73], and distributed energy resources (DERs) and MGs can be used to satisfy user needs via energy-management tools. SB lighting solutions have been shown to reduce energy consumption by 50% [72,73].

GBs and SBs are complementary components of SGBs [55]. SBs improve the performance of GBs while GBs improve the intelligence of SBs. GBs represent a holistic approach to constructing and operating environmentally conscious and resource-efficient structures, encompassing all stages from siting and design to construction, operation, maintenance, renovation, and eventual deconstruction. This augments the traditional focus on economic viability, utility, durability, and comfort within buildings [70,74]. The BMS is a key component of SBs and GBs. It was shown to provide up to 30% energy savings by monitoring, measuring, and optimizing building performance [70,72]. The BMS controls diverse functions including HVAC systems, chillers, and lighting management [72,73].

3.6. DP in MBs

Efforts to address the challenges with MBs center around effective management of power supply and consumption using techniques such as peak shaving, load reduction, DP, and efficiency models [75–77]. Numerous methods have been proposed for SGBs and MG systems [1,78]. Mohammed et al. [79] considered mixed-integer linear programming (MILP) for economic dispatch (ED) with grid-connected MGs to reduce operational costs and thermal energy usage. Smith et al. [80] used DP to improve the efficiency and performance of multi-carrier MG systems. A multi-carrier MG system provides more flexible, efficient, and intelligent energy management to lower costs and decrease thermal energy consumption. Kamal et al. [81] used MGs to optimize distribution network energy management. These approaches employ mechanisms such as DR, load shifting, energy storage, grid integration, predictive maintenance, and renewable energy integration.

Multiple MGs have been used to enhance system operation and reliability via improved energy consumption decision making [82,83]. In [8,9,76], SGBs were shown to improve energy efficiency and performance while reducing energy consumption. Homaei et al. [84] considered robust high-performance building designs in smart cities considering climate and occupant uncertainties. An energy-management system using an aggregator, MILP model predictive control (MPC), and Q-learning for an SB was proposed in [85] considering uncertainties in real-time data.

Wang et al. [27] employed a homogeneous ensemble prediction model for energy demand in an institutional building. Ding et al. [86] used a model to analyze the energy consumption in GBs in China by leveraging payment data. Load prediction for GBs was investigated in [87]. Historical data were used in an energy management system (EMS) to improve performance considering energy storage. Masburah et al. [88] estimated real-time uncertainty in building loads using Gaussian process (GP) learning. GBs with MGs were examined in an ED context.

Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP) [89] has emerged as an invaluable tool in understanding the impact of SGB innovations, particularly in the context of decision making. Gluszak et al. [72] studied the impact of SGB innovation on real estate markets using the AHP [90]. This shows the AHP method is relevant for DP in MBs. The prediction accuracy is based on three factors: the prediction method, the data quality, and the amount of data. A suitable prediction method combined with sufficient high-quality data can yield precise and dependable building performance prediction, including energy consumption for heating and cooling. The AHP is important as it aids in the assessment and prioritization of these factors, enabling more informed and effective decision making.

3.7. ML Methods Applied in MBs

ML methods such as ANN and RNN, and DL models such as unidirectional long short-term memory (ULSTM) and bidirectional LSTM, have been used for energy DP to improve the accuracy, robustness, and efficiency of MB modeling [9,27,67,77,91–94]. In [93], Olu-Ajayi et al. considered ANN, RL, and decision algorithms for energy storage, cost reduction, management, and DP. RNNs, ULSTMs, and bidirectional LSTMs were used in hybrid DL models to forecast energy demand in [68]. It was shown that bidirectional LSTMs can effectively capture energy consumption patterns in SGBs.

Amasyali et al. [31] examined ML models such as ANN, gradient boosting (GB), deep NN (DNN), random forest (RF), KNN, SVM, DT, and LR for energy consumption prediction in residential buildings using a large residential dataset. DNN was shown to be the best model, especially in forecasting annual building energy consumption. Godinho et al. [9] examined ML methods such as LR, PR, ANN, and SVM for SB cost reduction and performance improvement. They determined that ANNs provide a 10–20% improvement in forecasting heating demand compared to other methods. Zhao et al. [77] used the commercial solver MOSLEK 8.1 in MATLAB to obtain good MG accuracy with computational and operational efficiency while providing a cost reduction.

Peng et al. [95] explored Bayesian regularization (BR), Levenberg–Marquardt (LM), and ANN methods for commercial and residential building load forecasting. They evaluated the accuracy over different time periods and determined that ANNs provide the best day-ahead and hour-ahead forecasting results. Lu et al. [96] addressed DR in home energy management systems (HEMS) using RL and ANN methods [97]. Price and user energy cost prediction, smart home performance, and controllable and non-controllable loads were examined. Dagdugui et al. [8] employed an NN and learning algorithms for load forecasting.

Table 2 presents a performance comparison of ML algorithms considering eight metrics. Tables 3 and 4 present a comparison of research and review papers selected based on their relevance and importance. They provide a comprehensive perspective on the methods employed in the literature and indicate that AI systems play a pivotal role in MBs, facilitating advanced automation, optimization, and decision making. Figure 6 shows that these systems within MBs contribute to improved energy efficiency and occupant comfort, increased safety and security, and more effective facility management [44,75].

Table 2. ML algorithm performance comparison.

Reference	Computation Time	Accuracy	Efficiency	Energy Consumption	Cost	Uncertainty	Reliability	Training Speed
[8]	-	✓	✓	✓	-	-	-	-
[17]	✓	✓	-	✓	-	✓	-	-
[19]	-	✓	✓	✓	-	✓	-	-
[27]	✓	✓	-	-	-	-	-	✓
[28]	-	✓	-	-	-	-	-	-
[63]	-	-	-	✓	-	-	-	-
[66]	✓	✓	-	✓	✓	✓	-	-
[77]	✓	✓	✓	✓	✓	-	✓	-
[84]	-	-	✓	✓	✓	✓	-	-
[92]	-	✓	-	✓	✓	✓	-	✓
[93]	-	✓	✓	✓	-	-	-	-
[95]	-	-	-	✓	-	-	-	-
[96]	-	-	-	✓	✓	-	-	-
[98]	-	-	-	✓	-	-	-	-
[99]	✓	✓	-	✓	-	-	-	-
[100]	-	✓	-	✓	✓	-	-	-
[101]	-	✓	-	✓	✓	✓	-	-
This work	✓	✓	✓	✓	✓	✓	✓	✓

Table 3. Comparison of ML Methods.

ML Methods	Reference	Year	Model Components	Objectives
BR, LM, ANN	[8]	2019	SCRB	Building energy forecasting using an NN model
RT	[17]	2019	SBRS	Hybrid ML model based on ARIMA, logistic regression, and ANN for peak load forecasting during a day
Extreme GB, Bayesian optimization	[19]	2023	RES, PV direct-driven air-conditioner	Real-time energy DP
EBT	[27]	2018	BMS	Stability and prediction
SVM, MLP, CNN, DT, RF	[28]	2018	Autonomous car	Road image recognition
ADWIN, FSA, DDM	[99]	2020	RB	Automated modeling of residential appliances and agents
ANN	[30]	2020	Bicycle sharing station	Hybrid ML for bicycle sharing DR
Online algorithms	[63]	2017	HVAC system in an SB	Real-time occupancy for building automation
Hybrid DL	[66]	2014	SGB	Grid frequency regulation in a commercial building
Two-stage robust optimization	[77]	2018	DER, NMG	Improving power system resilience
MPC, Q-learning	[85]	2022	ESS, Aggregator, SB	Energy management of residential resources including TCLs, PV systems, and EVs
ANN, RL	[92]	2021	SS, HEMS, RES	Reducing energy cost, customer dissatisfaction, and grid overloading
ANN, GB, DNN, RF, Stacking, KNN, SVM, DT, LR	[93]	2022	RB	Predicting annual building energy consumption
RL	[95]	2020	SH	Adaptive home automation for energy DP
RL, ANN	[96]	2019	HEMS	Hour-ahead DR
CNN, ANN	[98]	2017	RB	Energy load forecasting
Hybrid models	[100]	2019	DER, MG	Energy system analysis using a taxonomy of models and applications

Table 4. ML in MBs.

Reference	Applications	Objectives	Year
[1]	RBs	Net-zero-energy building optimization and design	2021
[19]	SBs, SGs	DP analysis and optimization with a hybrid ML model	2023
[43]	SBs, SGs	Load forecasting with a hybrid ML model	2017
[59]	SBs, smart cities	Energy savings and efficiency	2020
[73]	SBs	ML method and big data analytics evaluation	2019
[88]	SGBs	Analysis of SUB features, e.g., automation	2019
[97]	Buildings	Building energy use forecasting using NNs	2019
[100]	Energy systems	ML models for energy systems and their applications	2019
[101]	SBs	Crowdsourcing for fault detection	2017
[102]	SBs	HEMS for energy reduction	2018
[103]	Mobile multimedia	Soft/hard frameworks	2017
[104]	Non-residential buildings	Energy analysis and optimization	2017
[105]	Commercial buildings	Electricity load forecasting	2017
[106]	GBs	Construction cost prediction	2022
[107]	SBs, smart cities	Intelligent environment evaluation	2018
[108]	SBs	DRL for energy management	2021
[109]	SB control	RL for energy and security control	2020
This work	MBs, energy systems	ML method evaluation	2023

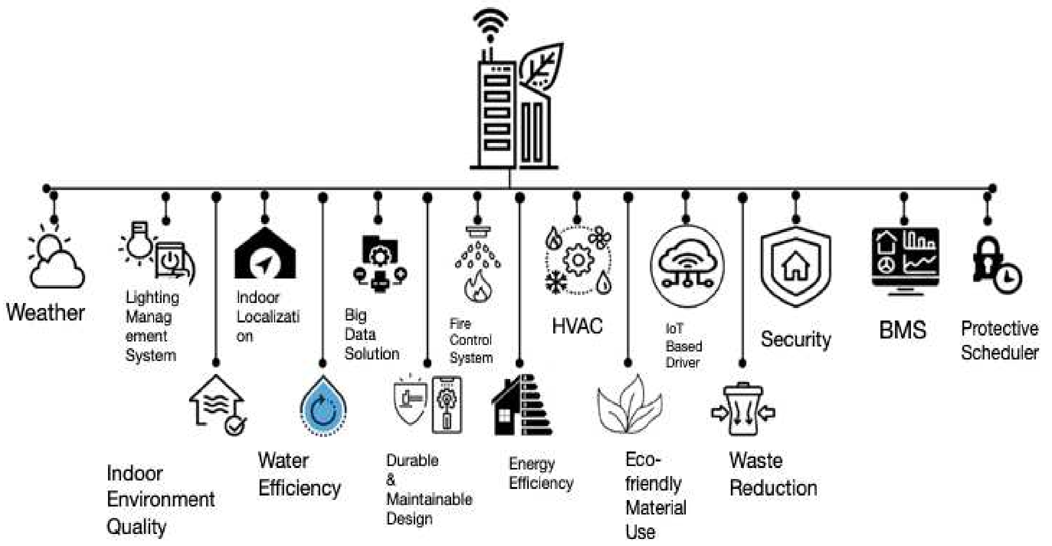

Figure 6. Artificial intelligence (AI) system components in modern buildings (MBs) [44,75].

3.8. Materials and Technologies for Energy Efficient Buildings

The selection of appropriate materials and technologies is important for sustainable and energy-efficient building design [110]. Innovative solutions are required to reduce energy consumption and the environmental impact. Hybrid multiple-criteria decision making (MCDM) [111] has been shown to be an effective methodology for assessing and selecting materials that align with energy efficiency objectives. It combines decision-making techniques to evaluate multiple criteria and the tradeoffs in material selection. MCDM provides a systematic framework to prioritize materials based on factors such as thermal performance, durability, cost-effectiveness, and environmental sustainability. In [112], a hybrid MCDM model was proposed to evaluate polymeric materials for flexible pulsating heat pipes. This contributes to the use of energy-efficient building materials and technologies by providing valuable insights for architects, engineers, and stakeholders in the construction industry. Hybrid MCDM has also been employed with ML methods for building applications [110,111,113].

- Model
  ML offers a variety of models for SB tasks such as DP, energy optimization, and fault detection. Hybrid MCDM can be used to evaluate ML models and select the most appropriate one for a building-related task based on criteria such as accuracy, interpretability, computational cost, and available data.
- Feature Selection
  Feature engineering and selection are crucial in building ML models. Hybrid MCDM can help choose the best set of features (variables) for a prediction or optimization task in a building context. This can lead to more efficient and accurate models.
- Algorithm Tuning
  ML algorithms have hyperparameters that need to be tuned for optimal performance. Hybrid MCDM can aid in selecting the best hyperparameter values considering the performance metrics and constraints specific to building applications.
- Data Preprocessing
  Building datasets can be complex with various types of data, e.g., sensor, weather, and occupancy data. Hybrid MCDM can guide decisions on data preprocessing such as handling missing data, data scaling, and outlier detection to ensure high-quality data for ML models.
- Ensemble Methods
  Ensemble ML models are often employed to improve prediction performance. Hybrid

MCDM can be used to determine the best ensembles considering the strengths and weaknesses of individual models.

- Model Evaluation
  Hybrid MCDM can assist in evaluating the performance of ML models. This includes the selection of appropriate evaluation metrics, e.g., MAE, RMSE, and F1-score, and weighting them based on their importance in the context of building applications.
- Risk Assessment
  In building management, there may be risks associated with ML approaches. Hybrid MCDM can help in assessing these risks and making decisions that balance factors such as accuracy, robustness, and potential negative impacts.
- Energy Optimization
  ML is commonly used for energy optimization in SBs. Hybrid MCDM can assist in choosing the right ML methods to optimize energy consumption considering factors such as building type, occupancy patterns, and available technologies.

In summary, hybrid MCDM can enhance the use of ML methods in building-related tasks by assisting in model and feature selection, algorithm tuning, and evaluation. This will help ensure that ML solutions are tailored to the specific requirements and constraints of SB applications, leading to more effective and efficient building management.

3.9. Datasets

It has been demonstrated that model accuracy depends on the method employed as well as data quality and quantity [97]. Thus, the availability of real historical datasets is important for effective building models. In [68], hybrid ML methods were used with two real energy consumption datasets to forecast energy consumption in SBs considering the appliances. ML was employed in a real hospital dataset in [49] for prediction and treatment purposes. In [9], a one-year real historical dataset with hourly measurements of occupancy profiles, solar gains through glazing, outdoor dry-bulb temperatures, and heating and cooling fluid temperatures was considered.

4. Conclusions

This paper examined ML methods for energy management prediction in modern buildings (MBs). It was observed that hybrid and ensemble ML methods such as support vector machines (SVM) combined with random forest (RF) outperform single prediction models. In particular, hybrid ML models can achieve up to 15% higher accuracy in energy consumption prediction than single ML models. The results presented show that ML methods can be used for accurate and efficient energy management in MBs. Furthermore, incorporating additional attributes in the dataset can improve energy prediction accuracy and efficiency.

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Abbreviations

The following abbreviations are used in this manuscript.

ADWIN	Adaptive Windowing
AI	Artificial Intelligence
AHP	Analytic Hierarchy Process
ALPLA	Adaptive and Lightweight Physical Layer Authentication
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto-Regressive Moving Average
BMS	Building Management System
BP	Back Propagation
BR	Bayesian Regularization
CART	Classification And Regression Tree
CNN	Convolutional Neural Network
CV	Cross-Validation
DDM	Drift Detection Method
DER	Distributed Energy Resource
DNN	Deep Neural Network
DP	Demand Prediction
DRL	Deep Reinforcement Learning
DT	Decision Tree
DTR	Decision Tree Regression
EBTs	Ensemble Bagging Trees
EC	European Commission
EV	Electric Vehicle
EU	European Union
ED	Economic Dispatch
EMS	Energy-Management System
ESN	Echo State Network
ESS	Energy Storage System
FL	Flexible Load
FSA	Fish Swarm Algorithm
GA	Genetic Algorithm
GB	Green Building
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GP	Gaussian Process
GRU	Gated Recurrent Unit
HEC	Hone Energy Calculator
HEMS	Home Energy-Management System
HVAC	Heating, Ventilating, and Air-Conditioning
IDC	International Data Corporation
IoTs	Internet of Things
KNN	K Nearest Neighbors
LASSO	Least Absolute Shrinkage and Selection Operator
LM	Levenberg–Marquardt
LR	Linear Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MB	Modern Building

MCDM	Multiple Criteria Decision Making
MDP	Markov Decision Process
MG	Micro-Grid
MILP	Mixed-Integer Linear Programming
MLP	Multi-Layer Perceptron
ML	Machine Learning
MSE	Mean Squared Error
MSVM	Multi-output SVM
MPC	Model Predictive Control
MTL	Multi-Task Learning
MWD	Multi-resolution Wavelet Decomposition
NLP	Natural Language Processing
NMG	Networked Micro-Grid
NN	Neural Network
NNR	Neural Network Regression
NSOB	Non-Stationary Operated Building
NZEB	Nearly Zero-Energy Building
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
PV	Photovoltaic
RB	Residential Building
RES	Renewable Energy Resource
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RR	Ridge Regression
RT	Regression Tree
SB	Smart Building
SBEM	Smart Building Energy Management
SBRS	Smart Building for Residential Sector
SCRB	Smart Commercial and Residential Building
SG	Smart Grid
SGB	Smart Green Building
SH	Smart Home
SL	Supervised Learning
SS	Storage System
SUB	Sustainable Building
SVD	Singular Value Decomposition
SVM	Support Vector Machine
SVR	Support Vector Regression
TCL	Thermostatically Controlled Load
UL	Unsupervised Learning
ULSTM	Unidirectional Long Short Term Memory
VoIP	Voice over Internet Protocol
WD	Wavelet Decomposition

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