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REVIEW
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Systematic Review of Deep Learning and Machine Learning for Building Energy

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The building energy (BE) management plays an essential role in urban sustainability and smart cities. Recently, the novel data science and data-driven technologies have shown significant progress in analyzing the energy consumption and energy demand datasets for a smarter energy management. The machine learning (ML) and deep learning (DL) methods and applications, in particular, have been promising for the advancement of accurate and high-performance energy models. The present study provides a comprehensive review of ML- and DL-based techniques applied for handling BE systems, and it further evaluates the performance of these techniques. Through a systematic review and a comprehensive taxonomy, the advances of ML and DL-based techniques are carefully investigated, and the promising models are introduced. According to the results obtained for energy demand forecasting, the hybrid and ensemble methods are located in the high-robustness range, SVM-based methods are located in good robustness limitation, ANN-based methods are located in medium-robustness limitation, and linear regression models are located in low-robustness limitations. On the other hand, for energy consumption forecasting, DL-based, hybrid, and ensemble-based models provided the highest robustness score. ANN, SVM, and single ML models provided good and medium robustness, and LR-based models provided a lower robustness score. In addition, for energy load forecasting, LR-based models provided the lower robustness score. The hybrid and ensemble-based models provided a higher robustness score. The DL-based and SVM-based techniques provided a good robustness score, and ANN-based techniques provided a medium robustness score.

Keywords: deep learning, machine learning, building energy, energy demand, energy consumption, smart grid, internet of things, data science

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INTRODUCTION

One of the essential aspects of smart buildings is to provide optimum living conditions following numerous standards and energy parameters (Al Dakheel and Tabet Aoul, 2017; Li et al., 2017). There is a need for energy consumption management to achieve the optimum comfort, cost, and tranquility in the buildings (Vázquez-Canteli et al., 2019). Therefore, several smart facilities and equipment are installed in the building to regulate the living condition. The major parts of energy consumption in buildings provide thermal and refrigeration comfort, i.e., cooling and heating systems, water supply

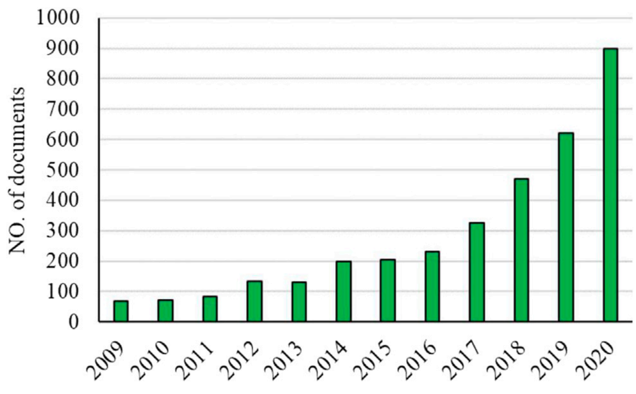

FIGURE 1 | Number of documents.

facilities, sanitary spas, lighting-related facilities, and so on (Faizollahzadeh Ardabili et al., 2016; Ma et al., 2017). In addition, different pieces of equipment are installed in each building depending on the type of building, each of which in turn consumes energy. Therefore, in each building, energy is used in different ways to face the needs of residents. Buildings are candidates for about forty percent of the total energy consumption (Vázquez-Canteli et al., 2019). The management of the energy in buildings can be considered as one of the important aspects of smart cities. The sustainability index in urban development can be carefully considered as a social function of energy generation and local consumption in each developing city. The sustainability index of urban development efficiently is a function of energy generation and direct consumption of each developing city. The energy consumption of buildings is responsible for a considerable value of energy consumption in an urban settlement (Ardabili et al., 2019a; Nosratabadi et al., 2019). There are several techniques aiming to accurately estimate and predict the energy production and consumption in the building sector (Mocanu et al., 2016; Li et al., 2017; Singaravel et al., 2018). In overall, at the building level, two types of necessary actions in this direction can be helpful. A series of models are based on physical principles to justify thermal dynamics and energy behavior in mathematical language. These models are the basic models and are characterized based on the type of building and effective parameters. Models developed based on statistical methods are other types of models that are used to estimate the energy consumption based on variables affecting climate and energy costs. From this perspective, the forecasting of demand and consumption is important in development of smart cities. Machine learning (ML)-based techniques, as a subset of artificial intelligence (AI), can provide a practical platform for modeling by considering a wide range of parameters (Fan et al., 2017). ML-based techniques have recently contributed significantly in implementing the reliable estimation models (Amasyali et al., 2018; Zou et al., 2018; Cai et al., 2019; Guiqing Zhang et al., 2020). Several researchers have employed ML-based techniques in different fields of area (Safdari Shadloo et al., 2021). Yahya et al. (2021) employed multilayer perceptron (MLP), radial basis function (RBF), cascade feedforward (CFF), and generalized regression neural networks (GRNN) for estimation of the thermal conductivity of water–alumina nanofluids (Yahya et al., 2021). Zhang et al. (2021) employed an AI-based optimization procedure to obtain the highest efficiency of an off-grid hybrid renewable energy scheme composed of wind, fuel cell, and hydrogen storage schemes (Weiping Zhang et al., 2021). Therefore, these techniques cover a wide range of scientific fields. **Figure 1** claims the exponential trend in implementing the ML-based techniques in this realm during the past decade. The main contribution of the present study is to peruse the use of novel ML-based techniques in forming the applications of smart cities in terms of energy. The scope covers the building energy (BE) demand and consumption and energy load prediction which are the key energy concerns in the building sector (Chou and Ngo, 2016; Fan et al., 2019; Chaobo Zhang et al., 2020).

In this way, there are several survey articles which have been developed with a little overlap in terms of the purpose of the study. Martinez et al. (2021) developed a survey article for analyzing the AI-based approach employed in distribution networks (Barja-Martinez et al., 2021). Hasan and Roy (2021) developed a review work by emphasizing on the application of DL-based techniques, transfer learning, active learning, and reinforcement learning for handling the cyber-physical building environment energy consumption (Hasan et al., 2021). In a review work by Mohapatra et al. (2021), ML-based and DL-based techniques are evaluated only for predicting the BE consumption (Mohapatra et al., 2021). Uzum et al. (2021), in a review work, evaluated the possible solutions with AI-, DL-, and ML-based optimization techniques for analyzing the effects of rooftop PV on distribution networks (Uzum et al., 2021). Vázquez-Canteli et al. (2019) developed a survey study to analyze the reinforcement learning techniques applied for demand response applications in the smart grid (Vázquez-Canteli et al., 2019). Panchalingam and Chan (2019) developed a survey study for describing and analyzing the energy use in smart buildings using the applications of ML- and DL-based techniques (Panchalingam and Chan, 2021). A number of recent surveys studied the application of machine learning in building energy. However, there is still a gap in the presence of a standard review article where the PRISMA statement is correctly adapted. In addition, an in-depth investigation on the accuracy of the model accuracy is still missing. Other differences are the taxonomy content, study concept, and the perspective of the study, as well as the main findings of the study. The limitations of the concepts used, as well as the study of a limited community of applications of ML-based techniques in previous studies, led to a more comprehensive study in the present survey to cover the weaknesses of previous studies. One of the main weaknesses in previous studies was the evaluation of ML-based and DL-based techniques in energy applications in building sectors. On the other hand, according to studies, the existence of a systematic review article based on a standard method that can extract all the strengths and weaknesses of using machine learning methods and deep learning in energy applications in the building, is missing. The PRISMA method is a method of preparing review articles that have not been discussed in this field. Accordingly, the present study presents a comprehensive systematic review based on the standard PRISMA method. The present study has taken steps to cover these weaknesses by providing evaluation methods and comparing different models in different applications. Accordingly, the present work has four main steps. The first step is to describe the main procedure of the searching and methodology for developing the base of the study. The second step is to analyze the studies with different ML- and DL-based techniques separately in different applications. The third step is to analyze the results and main findings including advantages and dis-advantages of each method in each application, and the final step is to summarize and conclude the main findings and suggestions of the study.

METHODOLOGY

This section qualifies how to study and the original taxonomy of the work. Given that this study is a review study, it is necessary to collect similar and related studies and categorize them according to the taxonomy of the work. Therefore, before explaining how to collect information and similar studies, we need to explain the main taxonomy of the article. This article is structured in eight main parts. The first part is the introduction so that we can have an initial introduction of the work and present the problem statement, the existing gaps in this field, and the purpose and justify the work. The second part is the methodology section, which explains how to do the study. The main mission of this article begins with the third section. The third section describes the studies conducted in the field of forecasting energy demand in buildings. This section has six sub-sections. First, the structure and description of artificial neural network (ANN) models, support vector machines (SVMs), hybrid models, and ensemble techniques are examined. In each subset, studies in this field are discussed in parallel. The fifth subdivision is related to the introduction of evaluation parameters, and the sixth subdivision is related to the presentation of the results of studies conducted in the field of forecasting energy demand in buildings. It should be noted that the description of the structure of the models is done once and in the next sections, only the studies are reviewed. The fourth section presents studies on energy consumption forecasting in buildings. This section has five subsets to express the studies performed with ANN models, SVM, hybrid models, and ensemble models and the results obtained. Therefore, the results of each section are reviewed and discussed within the same section. The fifth section presents studies on energy load forecasting in buildings. This section has five subsets to express the studies performed with ANN models, SVM, hybrid models, and ensemble models and the results obtained. The sixth section examines studies conducted by deep learning (DL) models in the BE sector. Due to the high importance of DL models, these models were separated from other machine learning models to be examined separately. This section also includes four subsets to express and describe the structure of recurrent neural networks (RNNs), long–short term memory (LSTM), and convolutional neural networks (CNNs) and the results obtained from these studies. The seventh section expresses the discussion, and the eighth section expresses the conclusion.

The procedure of data collection for review process adopts the PRISMA standard. According to Mosavi et al., (2020), the PRISMA method defines four main levels including: 1) identification, 2) screening, 3) eligibility, and 4) inclusion for developing a systematic review. According to the identification stage, an initial search was performed among the databases. Using Thomson Reuters Web-of-Science (WoS) and Elsevier Scopus, 350 of the most relevant articles are identified. The next level is screening the duplicate articles and choosing the relevant articles according to the title and abstract section. In this level, 70 articles have been identified. The next step is eligibility, to study the full text of articles by authors and to select the relevant articles by considering the eligibility for the final review process. In this level, 52 articles have been selected for the required evaluations. The final level of the PRISMA technique is to build the database of the study for qualitative and quantitative comparisons. The database of the present study includes 52 articles, for performing the required analyses. **Figure 2** presents the flowchart of forming the database of the current study using the PRISMA technique.

DEMAND PREDICTION IN THE BE SECTOR

Demand prediction in the BE sector is vital for planning and management purposes in the energy systems. This section presents studies developed for demand prediction using different ML methods in the building sector. **Table 1** proposes the top studies in the BE demand prediction using ML-based methods.

Ayoub et al. (2018) employed the ANN for forecasting microlevel energy supply and demand for buildings (Ayoub et al., 2018). Marmaras et al. (2017) developed an ANN-based technique for the estimation of the power demand of the building (Marmaras et al., 2017). Buratti et al. (2014) presented an ANN-based predictive model for the reduction of cooling energy demand in buildings (Buratti et al., 2014). Avni et al. (2014) presented a forecasting of Turkey energy demand using the ANN method (Es et al., 2014). Djenouri et al. (2019) presented a survey for the use of ANN-based methods for considering demand problems in smart buildings (Djenouri et al., 2020). Attanasio et al. (2019) developed the SVM method for the prediction of the building primary energy demand in comparison with ANN and DT methods (Attanasio et al., 2019). Paudel et al. (2015) developed the SVM method for forecasting the BE demand in the presence of the pseudo-dynamic approach (Paudel et al., 2015). Luo et al. (2019) developed a hybrid ML-based method for day-ahead prediction of BE demands based on the IoT-based big data platform (Luo et al., 2019). Martina et al. (2019) developed a hybrid prediction model for the estimation of daily global solar radiation to cope with the BE demand (Christy Martina and Amudha, 2019). Kokkinos et al. (2017) (query) developed hybrid ML-based methods for the prediction of energy demand in the building sector (Kokkinos et al., 2017). Popoola et al. (2015) developed a hybrid ML-based method for the prediction of

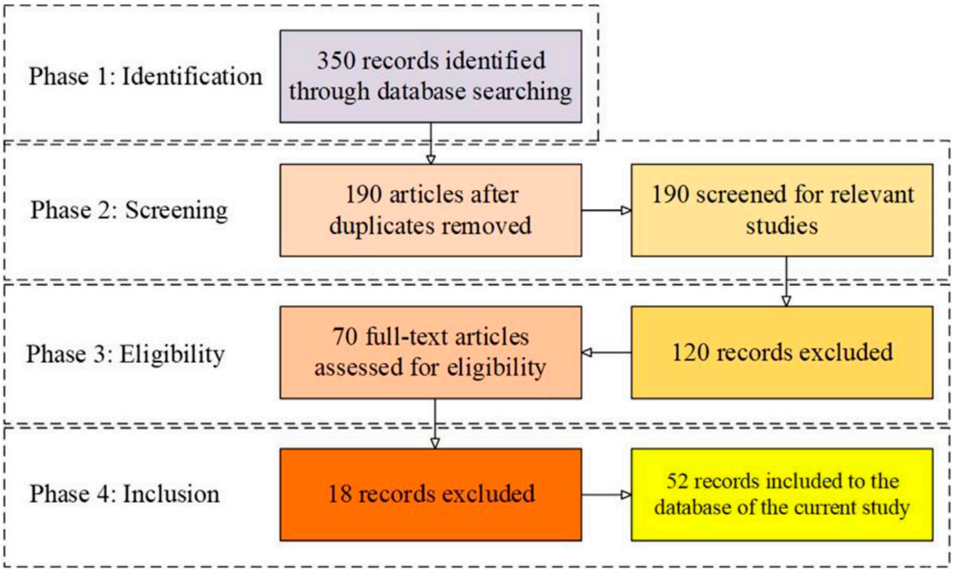

FIGURE 2 | Procedure of the PRISMA technique for the reviewing process.

TABLE 1 | Studies developed for BE demand prediction.

References	Contribution	Application	ML method(s)	Time period
Ayoub et al. (2018)	To present an ANN predictive model for forecasting microlevel energy supply and demand for buildings	Forecasting	ANN	Short term
Marmaras et al. (2017)	To present an ANN model for the estimation of the power demand of the building	Forecasting	ANN	Long term
Buratti et al. (2014)	To present an ANN predictive model for the reduction of the cooling energy demand in buildings	Optimization	ANN	Short term
Es et al. (2014)	To present a forecasting of Turkey energy demand using the ANN method	Forecasting	ANN	Long term
Djenouri et al. (2020)	A survey for the application of ANN-based methods for considering demand problems in smart buildings	Forecasting	ANN, SVM, GA, and SVR	Short term
Ahmad et al. (2018)	A comprehensive review on the application of ANN-based techniques for the estimation of energy demand in the building sector	Forecasting	ANN and SVM	Short term and Long term
Attanasio et al. (2019)	SVM method for the prediction of the building primary energy demand in comparison with ANN and DT methods	Forecasting	ANN, SVM, and DT	Short term
Paudel et al. (2015)	SVM method for forecasting BE demand in the presence of pseudo-dynamic approach	Forecasting	SVM	Short term
Luo et al. (2019)	To propose a hybrid ML method for day-ahead estimation of BE demands based on the IoT-based big data platform	Forecasting	k.means-ANN	Short term
Christy Martina and Amudha, (2019)	To develop a hybrid prediction model for the estimation of daily global solar radiation to cope with the BE demand	Forecasting	ANFIS	Long term
Kokkinos et al. (2017)	To develop hybrid ML techniques for forecasting the energy demand in building sectors	Forecasting	ANFIS and ANN	Long term
Popoola et al. (2015)	To develop a hybrid ML method for the estimation of energy savings associated with energy-efficient projects in building sectors	Forecasting	ANFIS and ANN	Short term
Raza et al. (2017)	The estimation of load demand using the hybrid ensemble method in the BE sector	Forecasting	Ensemble method	Short term
Yao Huang et al. (2019)	To propose an ensemble technique for the prediction of energy demands in building sectors	Forecasting	Ensemble method, ELM, and MLR	Long term

energy savings associated with energy efficient projects in the building sector (Popoola et al., 2015). Reza et al. (2017) provided a platform for the estimation of load demand using a hybrid ensemble method in the BE sector (Raza et al., 2017). Huang et al. (2019) employed a novel ensemble technique for the estimation of energy demand in the building sector (Yao Huang et al., 2019). Consequently, the major share and allocation of the studies conducted for the evaluation of the ML-based techniques for the BE sector's applications are related for forecasting and optimization purposes. Results

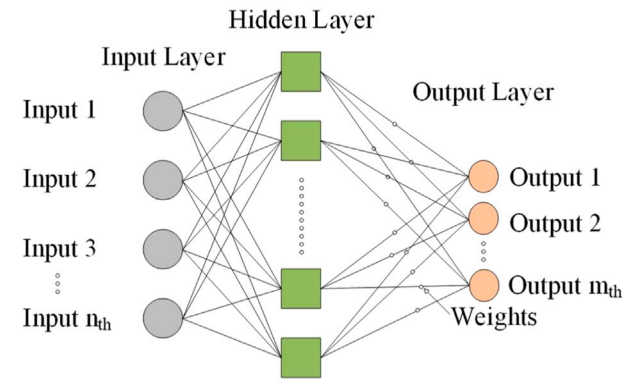

FIGURE 3 | Architecture of a simple ANN method.

claimed that the ML-based methods could successfully cope with the task.

ANN-Based Studies

The ANN can be considered as the practical and frequently used technique among other computational intelligence techniques. ANN-based methods can be successfully applied in forecasting, classification, modeling, clustering, error filtering, and optimization purposes. Artificial neurons make up the center unit of ANNs. Components of the ANN contain neurons, connections, weights and biases, and propagation function. **Figure 3** presents a simple form of an ANN method in the presence of the related compounds. In general, there are three steps for developing an ANN method: training, testing, and validating. Training is the most important step because it generates the ANN network.

The ANN contains connections which transport information from the previous node (which is called the output of a neuron) to the next node (which is called the input of a neuron). **Equation (1)** presents the total simple function of the ANN application in the presence of weights and biases.

$$I_j(t) = \sum_i O_i(t)w_{ij} + w_{0j}, \tag{1}$$

where I_j is the input value from the neuron i to neuron j in the presence of O_i as the output value of the neuron i. w_{ij} is the weight value, and w_{0j} is the related bias for the neuron j.

Recently, ANN-based techniques have been successfully used in the BE information sector for controlling, prediction, and optimization tasks. Ayoub et al. (2018) developed the ANN for the forecasting task in the energy demand sector for buildings for considering the building demand in the presence of a hybrid supply system. Accordingly, results claimed that the ANN could cope with the forecasting task. But there was a need for a robust model for preventing overfitting issues. Marmaras et al. (2017) presented an ANN-predictive model for the estimation of power demand in buildings. Six commercial buildings' electricity demand data were employed in order to train the ANN method. Data were collected from a business park during 1 year. Results claimed that the ANN provided higher accuracy and lower error values in comparing the model outputs and target values. Avni et al. (Es et al., 2014) developed the ANN method for the estimation of energy demand in Turkey using the population and area of the building. The developed ANN technique has been compared with linear regression in terms of accuracy and the robustness of methods. ANN provided higher accuracy than that for the LR technique. Buratti et al. (2014) performed a study for the optimization of the cooling energy demand using the ANN method in the presence of indoor thermal comfort. All of these studies have successfully employed the ANN to obtain the desired results. However, in further studies, researchers found that ANN-based methods can be successful only under certain conditions so that researchers have compared different methods with the ANN to reach an accurate model. The most common of these methods was the support vector-based methods.

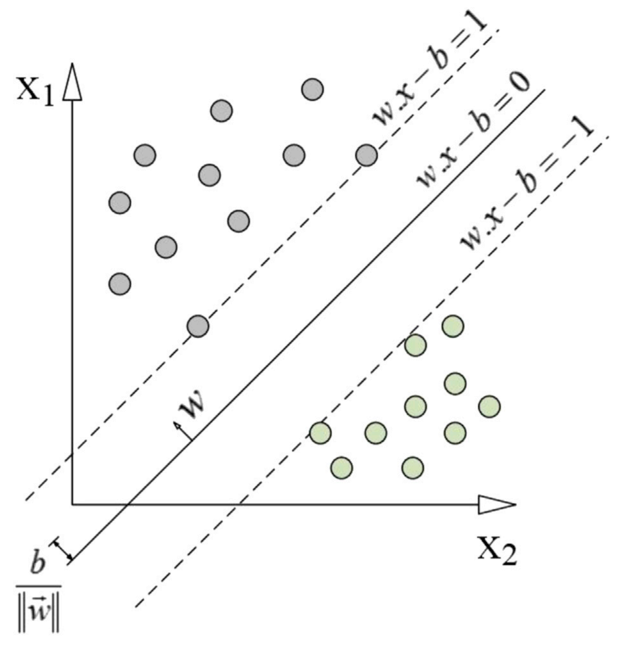

FIGURE 4 | Maximum margin hyperplane for a support vector.

Support Vector-Based Studies

Support vector-based machine learning methods are considered as supervised learning models which analyze data required for classification and regression purposes. Support vector-based machine learning builds a model to assign new examples for the training step in the presence of one or more categories. This makes support vector-based methods to be a non-probabilistic binary linear classifier. In the following, the mathematical model of a linear algorithm of the support vector-based machine learning can be found by considering a training dataset to be.

$(\vec{x_1}), \ldots, (\vec{x_n})$. Each $\vec{x_i}$ indicates a p-dimensional vector. The target is to propose the maximum-margin hyperplane. **Eq. 2** indicates any hyperplane as the set of the desired points.

$$\vec{w}.\vec{x} - b = 0, \tag{2}$$

where $\vec{w}$ is the normal vector to the hyperplane. $\frac{b}{\vec{w}}$ demonstrates the offset value of the hyperplane from the origin along the normal vector.

Originally, there are two types of margins, hard and soft margins. In a hard margin, the optimization problem is to minimize the $\vec{w}$ along $y_i(\vec{w}.\vec{x} - b) \geq 1$ for i = 1 . . . n. But in a soft margin, the optimization problem is a little different. In a soft margin, **Eq. 3** has to be minimized.

$$\left[\frac{1}{n}\sum_{i=1}^{n}\max\left(0, 1 - y_i\left(\vec{w}.\vec{x}_i - b\right)\right)\right] + \lambda||\vec{w}^2||, \tag{3}$$

where λ indicates the trade-off between enhancing the margin size and ensuring that the $\vec{x}_i$ lie on the correct side of the margin.

Figure 4 presents the maximum margin hyperplane for a support vector-based machine trained with samples which are called the support vectors.

Djenouri et al. (2020) developed a review work on the use of the SVM method in comparison with ANN and GA techniques for forecasting energy demands in buildings. The SVM method has been proposed for solving issues related to occupants and energy demands. This method has been introduced as a multi-disciplinary solution for energy demand problems in buildings. The SVM provided a higher performance than the ANN, but it can be an accurate model in energy demands by developing novel procedures. Ahmad et al. (2018) presented a review article in the application of support vector-based estimation techniques for forecasting the BE demand. Support vector-based techniques have been compared with ANN-based techniques, as the frequently employed techniques, in terms of accuracy and robustness. The study emphasizes on the highest robustness of support vector-based techniques compared with ANN-based methods in the BE demand sector. Paudel et al. (2015) developed a forecasting model for the BE demand using the SVM. The SVM has been introduced as a sensitive model to the selection of training data which made the author to employ dynamic time warping for training the SVM model.

In another study, Attanasio et al. (2019) developed the SVM method for the estimation of the building primary energy demand in comparison with ANN and DT methods for finding an accurate and robust method. The comparison factors were RMSE and accuracy factors. Based on results, the SVM could successfully do the task with a high reliability and performance compared with the ANN method, but it performed weak compared with the DT method. As a general note, it can be claimed that, in all cases, the SVM performs better than the ANN method. But, as is reported in the study by Attanasio et al. (2019), there is another method which can perform better than the SVM method for forecasting tasks. RF-based methods can be considered with a higher performance than the ANN and SVM. RF is an ensemble-based learning technique. The following sections present a brief description about hybrid and ensemble-based methods.

Hybrid-Based Studies

Hybrid methods are appeared for generating robust techniques by combining single methods for different purposes such as prediction, classification, and optimization purposes. The main aim is to collect the advantages of different methods and eliminate the disadvantage of methods. In most cases, hybrid methods compose one prediction method as the base method and one optimization method (as the complementary or second method) for increasing the accuracy of the prediction method. The most popular hybrid method is the ANFIS. The ANFIS employs fuzzy rules and ANN architecture for obtaining a sustainable prediction model. **Figure 5** presents a simple algorithm of developing a hybrid method. Recently, these methods have been frequently used in the prediction of energy demand in the building sector.

Luo et al. (2019) developed a hybrid k-means-ANN method for the estimation of the BE demand using a platform based on IoT-based big data. The proposed method could perform the task in the presence of IoT sensors for training the ANN method. Martina et al. (Christy Martina and Amudha, 2019) developed an ANFIS method for the prediction of daily global solar radiation in line with a proper solution for BE demand problems in the presence of meteorological parameters. The proposed ANFIS model has been compared with the statistical models in terms of accuracy and correlation values. In another study, Kokkinos et al. (2017) developed the ANFIS method for the prediction of the future energy demand of buildings for obtaining a future perspective form the BE balance. The proposed ANFIS method has been compared with the ANN and fuzzy cognitive map method in terms of RMSE, MAPE, and MAE. The performance of the ANFIS model was significantly higher than other methods. In another study, Popoola et al. (2015) developed an ANFIS method in comparison with the ANN technique for the prediction of energy savings in the building sector. The evaluation performance was determination coefficient (R2). The ANFIS method provided the best performance due to its hybrid advantages.

Ensemble-Based Studies

Ensemble-based methods, or in other words multiple classifiers, are supervised learning algorithms which have been employed in order to improve the classification accuracies. Developing an efficient ensemble method requires determination of an effective combination of classifiers for elimination of their weakness. These methods have an important difference compared with hybrid methods. Ensemble methods benefit different training algorithms for enhancing the training accuracy for generating a higher performance in the testing phase. Ensemble methods in fact allow for different training algorithms for generating flexible training (ref. Advances in machine learning modeling, Hybrids, and Ensembles). Boosting and bagging are most frequently used ensemble methods. This technique is also frequently employed in energy demand prediction in the building sector. Raza et al. (2017) developed an ensemble method including the neural ensemble, Bayesian model, and wavelet transform for the estimation of photo voltaic application in the energy demand for the building sector. This technique has been compared in the

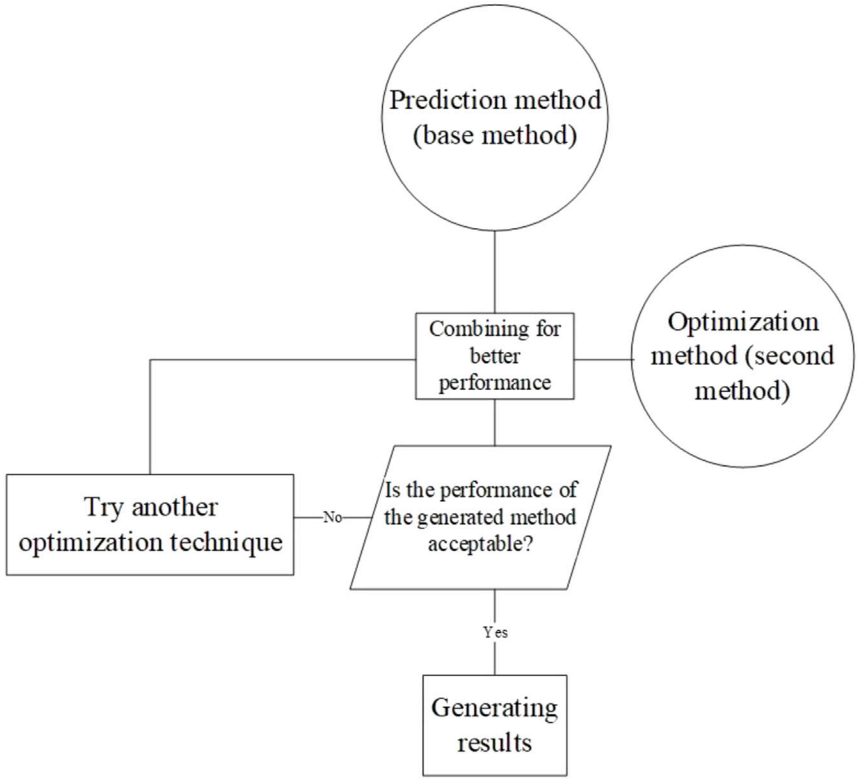

FIGURE 5 | Simple algorithm of developing a hybrid technique.

TABLE 2 | Model evaluation criteria.

Index	Description
$MSE = \frac{1}{N}(\boldsymbol{P} - \boldsymbol{A})^2$	P = predicted values
$RMSE = \sqrt{\frac{1}{N}(\boldsymbol{P} - \boldsymbol{A})^2}$	A = Actual values
$MAE = \frac{1}{N}\lvert\boldsymbol{P} - \boldsymbol{A}\rvert$	N = number of data
$MAPE = 100 \times \frac{1}{N}\lvert\frac{\boldsymbol{P}-\boldsymbol{A}}{\boldsymbol{A}}\rvert$	
$Accuracy = \frac{\textit{True p}+\textit{True n}}{\textit{True p}+\textit{True n}+\textit{False p}+\textit{False n}}$	p = positive
	n = negative
$Reliability = \frac{\sigma_T^2}{\sigma_X^2}$	T = True scores
	X = Errors of measurements
$Sustainability = \lvert 1 - \frac{\textit{Testing error}-\textit{Training error}}{\textit{Training error}}\rvert$	$0 \leq \boldsymbol{Sustainability} < 1$

MSE = An index to indicate the average of the squares of the deviations from the actual value.
RMSE = An index to indicate the difference between the target and output values.
MAE = An index to indicate the average vertical distance between the target and output values.
MAPE = An index to indicate the relative average vertical distance between the target and output values.
Accuracy = An index for measuring the statistical bias value.
Reliability = An index for measuring the overall stability of an experiment
Sustainability = An index for measuring the difference between testing and training errors

term of the nRMSE with different single and hybrid machine learning techniques. The selected ensemble method could successfully forecast the demand parameters and enhance the reliability of the method significantly. Huang et al. (Yao Huang et al., 2019) developed a novel ensemble method by employing extreme gradient boosting, MLR and ELM for developing an SVR method in the presence of a historical energy comprehensive variable. Outputs have been evaluated using RMSE and MAE parameters. According to the findings, the proposed ensemble method significantly provided a higher performance than single methods.

Criteria for Evaluations

The success of the discussed methods has been evaluated based on how capable the developed techniques are in generating most accurate predictions, detection, optimization, and monitoring of the process in terms of their statistical performance accuracy. **Table 2** presents the most common evaluating factors used for comparing the efficiency of the discussed techniques.

Results

Table 3 gives a summarized comparison about the accuracy, reliability, and sustainability of techniques developed for the BE demand prediction. The accuracy index has been obtained through the performance indexes related to the training phase, and reliability has been obtained from the performance indexes related to the testing phase. But, the sustainability index was a little different and has been obtained by comparing reliability, accuracy, processing time, and other factors which have been considered by outputs and findings of the reviewed articles.

As is clear from **Table 3**, ANN-based methods provide the lowest sustainability, and hybrid and ensemble-based methods

TABLE 3 | The comparison findings of techniques for BE demand.

Method	Application	Accuracy	Reliability	Sustainability	References
ANN	Regression	++	+	+	Ayoub et al. (2018)
ANN	Regression	+	+	+	Marmaras et al. (2017)
ANN	Optimization	++	++	+	Buratti et al. (2014)
ANN	Regression	++	+	+	Es et al. (2014)
ANN	Regression	+	+	+	Djenouri et al. (2020)
SVM	Regression	++	++	++	Djenouri et al. (2020)
GA	Regression	++	+	+	Djenouri et al. (2020)
ANN	Regression	+	+	+	Ahmad et al. (2018)
SVM	Simulation	++	++	++	Ahmad et al. (2018)
ANN	Simulation	++	+	+	Attanasio et al. (2019)
SVM	Regression	++	++	++	Attanasio et al. (2019)
DT	Regression	+++	++	++	Attanasio et al. (2019)
SVM	Regression	++	++	++	Paudel et al. (2015)
k.means-ANN	Regression	+++	++	++	Luo et al. (2019)
ANFIS	Regression	+++	++	++	Christy Martina and Amudha, (2019)
ANFIS	Regression	+++	+++	++	Kokkinos et al. (2017)
ANN	Regression	+	+	+	Kokkinos et al. (2017)
ANFIS	Regression	+++	+++	+++	Popoola et al. (2015)
ANN	Regression	++	+	+	Popoola et al. (2015)
Ensemble	Regression	+++	+++	+++	Raza et al. (2017)
Ensemble	Regression	+++	+++	++	Yao Huang et al. (2019)
ELM	Regression	+++	++	++	Yao Huang et al. (2019)
MLR	Regression	++	+	+	Yao Huang et al. (2019)

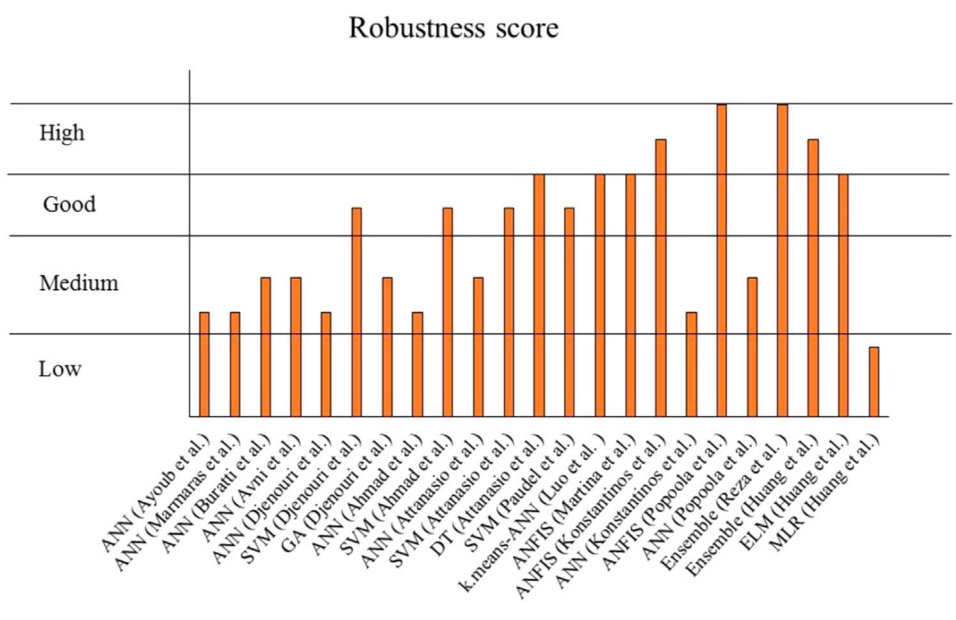

FIGURE 6 | Robustness score for energy demand forecasting methods.

provide the highest sustainability. In order to better understand and discuss the power of each method, it has been employed an index called robustness. This index has been provided as a novel index for describing the strength of each method based on their accuracy, reliability, and sustainability values. **Figure 6** presents a concluded graph for each technique, according to their robustness. **Figure 6** has been categorized into four limitations including high, good, medium, and low robustness score to describe the capability and strength of each method based on our own observations and understandings from conclusion and results of each study.

As is clear from **Figure 6**, for energy demand forecasting, hybrid and ensemble methods are located in the high robustness range, SVM-based methods are located in good robustness limitation, ANN-based methods are located in medium robustness limitation, and linear regression models are located in low robustness limitations.

TABLE 4 | Studies developed by ML techniques for forecasting BE consumption.

References	Contribution	Application	ML method	Time period
Finck et al. (2019)	To develop a model predictive controller using the ANN technique for forecasting BE consumption	Forecasting	ANN	Short term
Katsanou et al. (2019)	To develop the ANN technique for forecasting BE consumption in term of lightening systems	Forecasting	ANN	Short term
Sharif and Hammad (2019)	To present an ANN network to explore complex BE consumption in the presence of dataset extracted from the simulation-Based procedure	Forecasting	ANN	Short term
Ferlito et al. (2015)	To develop an ANN method for the prediction of BE consumption	Forecasting	ANN	Long term
Chammas et al. (2019)	To explore for proposing an accurate ML method for the prediction of BE consumption	Forecasting	ANN, LR, and SVM	Short term
Zeng et al. (2019)	To develop the ML-based method for forecasting of electricity consumption in building	Forecasting	ANN, SVM, and MLR	Short term and Long term
Xiaoyu Huang et al. (2019b)	To develop the SVM technique for forecasting of energy consumption for the production of hot asphalt	Forecasting	SVM	Long term
Dong et al. (2005)	To develop the SVM technique for the estimation of BE consumption	Forecasting	SVM	Long term
Chou and Tran, (2018)	To present a comprehensive review study for evaluating ML methods for the estimation of BE consumption	Forecasting	Hybrid SARIMA-MetaFA-LSSVR and SARIMA-PSO-LSSVR	Short term
Solgi et al. (2019)	To develop a hybrid hierarchical fuzzy multiple-criteria group decision-making for ranking the forecasting methods of BE consumption	Clustering	hybrid hierarchical fuzzy multiple-criteria decision-making	Short term
Goudarzi et al. (2019)	To develop a novel hybrid technique to estimate BE consumption from supplied data, accurately	Forecasting	Hybrid ARIMA-SVR and PSO	Short term
Silva et al. (2019)	To propose ensemble methods for forecasting BE consumption	Forecasting	RF, GBRT, and Adaboost	Short term
Zhang et al. (2018)	To develop a study for comparing the performance of ensemble and single methods for the prediction of energy consumption in the BE sector	Forecasting	RF	Long term
Papadopoulos et al. (2018)	To develop a tree-based ensemble technique for the estimation of BE consumption	Forecasting	FR, ERT, and GBRT	Short term

BE CONSUMPTION PREDICTION

BE consumption is a factor indexed by watt-hours which is considered as a functional unit of energy, consumed in a specific period of time (e.g., daily, monthly, etc.). This factor can be calculated by multiplying BE load values by the number of consumption hours (Badea et al., 2014). BE consumption is considered as one of the most effective factors for designing sustainable instruments in the building sector and can help policy makers in taking a future perspective. Therefore, forecasting tools can play an effective role in this field. **Table 4** collects and presents the most important studies developed with energy consumption prediction purposes in the building sector using ML techniques.

ANN-Based Studies

Finck et al. (2019) proposed the ANN method in the presence of a model predictive controller for the estimation of BE consumption. The ANN could successfully cope with the prediction task and could optimize the controlling process which was sustainable from the economic aspect. Katsanou et al. (2019) proposed the ANN technique for the estimation of the internal lighting system in a real condition in the presence of the user preferences. The ANN could successfully predict the target values. In another study, Sharif and Hammad (2019) proposed an ANN technique for forecasting BE consumption data exported from the simulation-based multi-objective optimization method. The study emphasizes on proposing a robust estimation technique for BE consumption. The proposed ANN technique consumes less processing time and high sustainability.

Ferlito et al. (2015) developed the ANN method for the prediction of the real energy demand of a generic building in the presence of a monthly historical dataset related to BE consumption. Main findings have been analyzed using the root mean square percentage error (RMSPE). According to the findings, the ANN was a proper tool for forecasting energy consumption indexes. As is clear and previously mentioned, the accuracy of the ANN is not enough for covering all datasets with different dimensions. There is a need for more accurate methods. One of these methods is the support vector-based technique which can be called as the frequently used techniques for the prediction of BE consumption.

Support Vector-Based Methods

Chammas et al. (2019) proposed a study for finding the estimation of the BE consumption in the presence of data exported from the IoT technique employed in building sectors. ML-based techniques containing the SVM and ANN have been compared with linear regression in terms of R2, MAPE, and RMSE. The database included three main sectors including no-light data, no-date data, and weather-only data for exploring proper variables on the simulation process. According to the findings, the SVM followed by the ANN has a higher performance than that for the linear regression model. Zeng et al. (2019) presented a comparative study for proposing a predictive method for forecasting electricity consumption in building sectors among ANN, SVM, and MLR methods. Results have been analyzed using the RMSE. Accordingly, the SVM could successfully generate accurate results. In a similar way, Huang et al. (Xiaoyu Huang et al., 2019) proposed the SVM method in comparison with the kernel principal component analysis for the estimation of energy consumption for producing hot mix asphalt as a part of building sector materials. Fuel consumption and prediction error values have been employed control values for evaluating results. The SVM presented accurate results within an acceptable error range. Also, Dong et al. (2005) developed the SVM technique for the estimation of BE consumption in China. The dataset was related to the Chinese National Bureau of Statistics in thirty provinces. Evaluations for reaching a best model architecture have been performed using MSE and R2 values. Accordingly, the SVM could successfully cope with the task.

Hybrid-Based Methods

Chou et al. (Fenza et al., 2019) proposed a hybrid SARIMA-MetaFA-LSSVR and SARIMA-PSO-LSSVR techniques for the prediction of BE consumption. Results have been evaluated using the correlation coefficient, RMSE, MAE, and MAPE factors and compared single (the ANN method), ensemble (bagging-ANN), and hybrid methods. Accordingly, the proposed hybrid methods could cope with the task as by providing the sustainability value for the prediction phase. Also, it has been observed that the ensemble method has higher accuracy than the single method, and the hybrid technique has higher accuracy than the ensemble method. In another study, Solgi et al. (2019) proposed an innovative hybrid hierarchical fuzzy multiple-criteria group decision-making for ranking the prediction methods in the presence of economic and environmental criteria and market-related and technical advantages. The desired technique could successfully cope with the defined task. Goudarzi et al. (2019) developed a novel hybrid forecasting model based on ARIMA-SVR and PSO for accurately forecasting BE consumption in the presence of the supplied data. Results have been analyzed using the RMSE, MAE, and MAPE. Accordingly, the hybrid method could provide an accurate forecasting platform compared with PSO-SVR and ARIMA.

Ensemble-Based Studies

Silva et al. (2019) presented a study for the evaluation of the performance of three ensemble methods containing RF, gradient-boosted regression trees, and Adaboost. Evaluations propose that employing ensemble methods can be one of the proper solutions for the problem rising from short-term forecasting. In a similar way, Zhang et al. (2018) proposed a comparison of the performance of ensemble and single techniques for proposing a proper prediction method for the prediction of the BE consumption. The developed methods were the linear regression, SVM-based model, random forest, and XGBoost algorithm. Comparisons have been conducted using the RMSE, R2, and MAE. Accordingly, the XGBoost algorithm followed by RF provided a higher performance than the SVM and linear regression. Papadopoulos et al. (2018) employed tree-based ensemble methods including RF, ERTs, and GBRTs for the prediction of energy consumption in the BE sector. Evaluations have been performed using MSE, MAE, and MAPE factors. Accordingly, GBRTs could successfully improve the average energy consumption, significantly.

Results and Discussion

Table 5 gives a brief comparison for the accuracy, reliability, and sustainability of the models developed for forecasting the BE consumption.

Figure 7 presents a concluded analytical comparison for each model according to their robustness. **Figure 7** has been separated into four limitations including high, good, medium, and low robustness scores to describe the capability and strength of each model according to our observations and understandings from conclusion and findings of each study.

According to **Figure 7**, for energy consumption forecasting, DL-based, hybrid, and ensemble-based models provided the highest robustness score. ANN, SVM, and single Ml-based models provided the good and medium robustness, and LR-based models provided the lower robustness score.

BE LOAD PREDICTION

BE load is a factor indexed by watt which is considered as a functional unit of power. This factor refers to the amount of electricity required to operate an electrical device at any given moment (Salih, 2020). The BE load is another significant aspect in the BE information sector. Recently, predictive methods have been employed for forecasting the energy load for obtaining sustainable conditions in the BE sector. **Table 6** presents top ML methods employed for forecasting the energy load in building sectors.

ANN-Based Studies

Dan et al. (Dan and Phuc, 2018) proposed the ANN method for forecasting the energy load in building sectors. Results of the ANN method have been evaluated using the RMSE factor and compared with MLR as a control method. The ANN could successfully cope with the forecasting task and provide a sustainable network for generating desired values. In another study, Yuce et al. (2017) developed the ANN method for the estimation of electricity load in the presence of current energy demand and social parameters. Multiple regression analysis and principal component analysis have been employed for choosing the proper input parameters. Results have been evaluated using the correlation coefficient and average percentage error values. The ANN could provide acceptable output values compared with actual values. Deb et al. (2016) proposed an ANN method for forecasting cooling load in the building sector in the presence of energy consumption data. Results have been evaluated using R2 values. The ANN could successfully cope with the forecasting task by its ability to train and estimate the next day energy consumption in the presence of data related to five previous days as input variables. In another study, Ahmad et al. (2019) developed GPR, ANN, and LR techniques for forecasting the medium-term horizon cooling load in building sectors in order to optimize the BE consumption. Methods have been compared in terms of correlation coefficient, MAPE, and coefficient of variation. As a result, GPR followed by the ANN provided the highest estimation accuracy in comparison with LR.

TABLE 5 | The comparison results of methods for BE consumption.

Method	Application	Accuracy	Reliability	Sustainability	References
ANN	Regression	+	+	+	Finck et al. (2019)
ANN	Regression	++	+	+	Katsanou et al. (2019)
ANN	Regression	+	+	+	Sharif and Hammad, (2019)
ANN	Regression	+	+	+	Ferlito et al. (2015)
ANN	Regression	++	+	+	Chammas et al. (2019)
LR	Regression	+	+	+	Chammas et al. (2019)
SVM	Regression	++	++	++	Chammas et al. (2019)
ANN	Regression	+	+	+	Zeng et al. (2019)
SVM	Regression	++	++	++	Zeng et al. (2019)
MLR	Regression	++	+	+	Zeng et al. (2019)
SVM	Regression	++	++	++	Xiaoyu Huang et al. (2019b)
SVM	Regression	++	++	+	Dong et al. (2005)
SARIMA-MetaFA-LSSVR	Regression	+++	+++	+++	Chou and Tran, (2018)
SARIMA-PSO-LSSVR	Regression	++	++	++	Chou and Tran, (2018)
HFMCD	Regression	+++	+++	++	Solgi et al. (2019)
Hybrid ARIMA-SVR-PSO	Regression	+++	+++	+++	Goudarzi et al. (2019)
ARIMA	Regression	++	++	+	Goudarzi et al. (2019)
SVR-PSO	Regression	+++	+++	++	Goudarzi et al. (2019)
RF	Regression	+++	++	++	Silva et al. (2019)
GBRT	Regression	+++	+++	+++	Silva et al. (2019)
Adaboost	Regression	++	++	++	Silva et al. (2019)
RF	Regression	+++	+++	++	Zhang et al. (2018)
RF	Regression	+++	++	++	Papadopoulos et al. (2018)
ERT	Regression	++	++	++	Papadopoulos et al. (2018)
GBRT	Regression	+++	+++	+++	Papadopoulos et al. (2018)

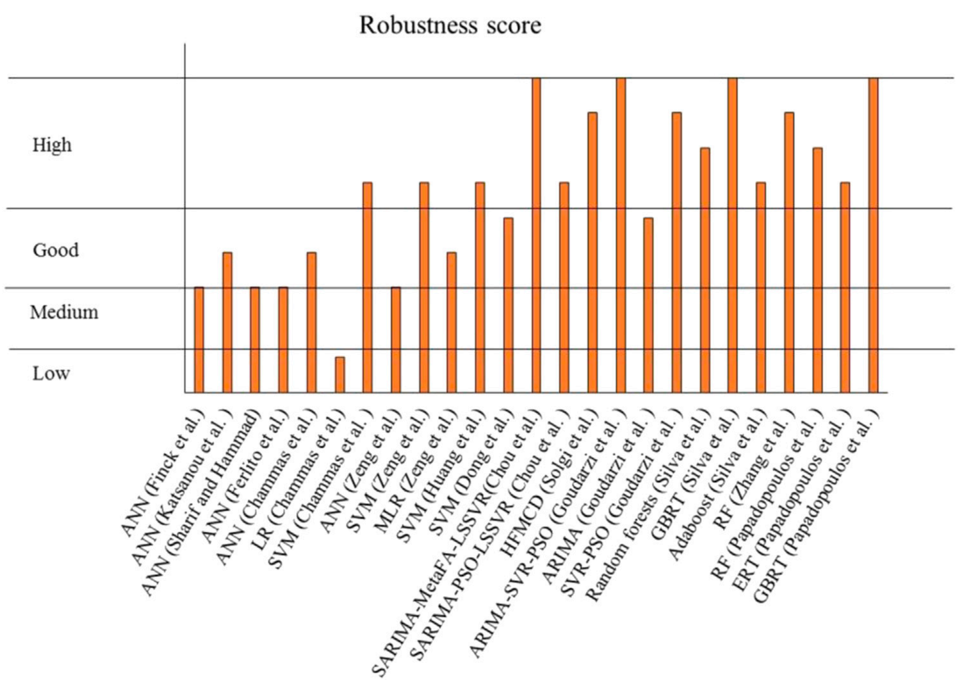

FIGURE 7 | Robustness score for BE consumption prediction methods.

Hybrid-Based Studies

Le et al. (2019) developed hybrid ML methods for proposing an accurate predictive model for estimating the heating energy load in the building sector. Results have been compared using R2, RMSE, and MAE factors. Based on results, employing hybrid methods has a significant effect on increasing the accuracy of a

TABLE 6 | Studies developed for forecasting energy load in the building sector.

References	Contribution	Application	ML method	Time period
Dan and Phu, (2018)	To develop the ANN method in comparison with MLR for the prediction of BE load	Forecasting	ANN	Short term
Yuce et al. (2017)	To develop the ANN method for the estimation of energy load in the presence of current electricity demand and social parameters	Forecasting	ANN	Long term
Deb et al. (2016)	To develop the ANN method for forecasting cooling load energy in building sectors	Forecasting	ANN	Long term
Ahmad et al. (2019)	To develop Gaussian process regression, ANN, and LR to estimate the medium-term horizon cooling load in building sectors	Forecasting	GPR, ANN, and LR	Short term
Zhu et al. (2019)	To develop ensemble ML methods for forecasting heating and cooling loads in the BE sector	Forecasting	RF, SVM, and LR	Long term
Le et al. (2019)	To develop a comparative study for forecasting the heating energy load of building sectors	Forecasting	PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN	Short term
Seyedzadeh et al. (2019)	To develop ensemble and single ML methods for the estimation of BE loads	Forecasting	SVM, RF, ANN, GBRT, and XGBoost	Short term
Bui et al. (2020)	To develop a hybrid ML method for accurate prediction of heating energy load in building sectors	Forecasting	ANN, M5rule, and GA-M5rule	Short term
Ngo (2019)	To predict different ensemble ML methods for forecasting cooling energy load in building sectors	Forecasting	ANN-SVR, ANN-LR, CART-SVR, CART-LR, SVR-LR, ANN-bagging, and ANNs + CART + SVR	Short term

single method. As a result, ANN-GA provided the highest performance among other techniques.

In another study, Bui et al. (2020) developed an innovative hybrid GA-M5rule method for forecasting cooling energy load in the building sector. The proposed method has been compared with the ANN and M5rule in terms of R2, MAE, and RMSE factors. Based on results, the proposed hybrid method could successfully increase the accuracy of forecasting.

Ensemble-Based Studies

Zhu et al. (2019) developed the RF method as one of the most popular ensemble methods in comparison with linear regression and SVM methods in terms of MAPE and MAE in the presence of datasets related to heating and cooling loads in the building sector. Based on results, RF followed by the SVM provided the highest prediction performance. Seyedzadeh et al. (2019) developed ensemble and single ML methods including the SVM, RF, GBRT, XGBoost, and ANN for the estimation of BE loads in the presence of datasets related to simulated BE which have been generated in EnergyPlus and Ecotect. Results have been evaluated using R2, RMSE, and MAE values. As a result, in a complex dataset, ensemble methods provide the highest accuracy in comparison with single techniques, such that GBRT followed by XGBoost provided the highest performance and accuracies. But in a simple dataset, the single SVM method provided the best accuracy. Ngo (2019) developed different ensemble methods for the estimation of cooling energy loads in building sectors. Results have been compared using R2, MAPE, and RMSE. As a result, the ensemble bagging ANN method could provide the highest prediction performance in comparison with other techniques.

Results and Discussion

Table 7 presents a brief comparison about the accuracy, reliability, and sustainability of methods developed for forecasting the energy load in the building sector.

Supplementary Figure S8 presents a concluded indicator for each method based on their robustness. **Supplementary Figure S8** has been separated into four limitations including high, good, medium, and low robustness scores to evaluate the capability and strength of each technique based on our own observations and understandings from conclusion and findings of each study. According to **Supplementary Figure S8**, for energy load forecasting, LR-based models provided the lower robustness score. The hybrid and ensemble-based models provided a higher robustness score. The DL-based and SVM-based techniques provided a good robustness score, and ANN-based techniques provided a medium robustness score.

DEEP LEARNING METHODS IN THE BUILDING INFORMATION SECTOR

Recently, DL techniques have been employed to be the most accurate methods for analyzing, predicting, and optimizing purposes in different fields of science. One of the most impressive fields is the building information sector. Various studies have successfully developed DL techniques for handling the building information sector. **Supplementary Table S8** presents the most important and top research studies in application of DL techniques in the building information sector.

Recurrent Neural Network-Based Studies

The RNN has been developed in order to handle sequences and patterns such as text, handwriting, and speech. RNN works based on cyclic connections in the structure and imports recurrent computations as input data. The RNN is generally based on the standard ANN that has been extended across time by having edges which feed into the next time step instead of into the next layer in the same time step. **Supplementary Figure S9** shows the architecture of the RNN. Additional explanations about the RNN

TABLE 7 | The comparison results of methods for energy load in building sectors.

Method	Application	Accuracy	Reliability	Sustainability	References
ANN	Regression	+	+	+	Dan and Phuc, (2018)
ANN	Regression	++	+	+	Yuce et al. (2017)
ANN	Regression	+	+	+	Deb et al. (2016)
GPR	Regression	++	++	+	Ahmad et al. (2019)
ANN	Regression	++	+	+	Ahmad et al. (2019)
LR	Regression	+	+	+	Ahmad et al. (2019)
RF	Regression	+	+	+	Zhu et al. (2019)
SVM	Regression	++	++	++	Zhu et al. (2019)
LR	Regression	+	+	+	Zhu et al. (2019)
PSO-ANN	Regression	++	+	+	Le et al. (2019)
GA-ANN	Regression	+++	+++	++	Le et al. (2019)
ICA-ANN	Regression	++	+	+	Le et al. (2019)
SVM	Regression	++	++	++	Seyedzadeh et al. (2019)
RF	Regression	+++	+++	++	Seyedzadeh et al. (2019)
ANN	Regression	++	+	+	Seyedzadeh et al. (2019)
GBRT	Regression	+++	+++	+++	Seyedzadeh et al. (2019)
ANN	Regression	+	+	+	Bui et al. (2020)
M5rule	Regression	++	++	++	Bui et al. (2020)
GA-M5rule	Regression	+++	+++	+++	Bui et al. (2020)
ANN-SVR	Regression	++	++	++	Ngo (2019)
ANN-bagging	Regression	+++	+++	+++	Ngo (2019)
ANNs + CART + SVR	Regression	+++	+++	++	Ngo (2019)

method have been presented in our previous study entitled the "list of DL techniques" (Ardabili et al., 2019b; Mosavi et al., 2020).

Hribar et al. (2019) developed a comparative exploration for analyzing the forecasting performance of RNN and LR models for the estimation of the urban natural gas demand. MAE and MAPE performance factors have been employed for evaluating the obtained results. As a result, the RNN could provide the best performance compared with that of the LR method. Kim et al. (2019) developed an RNN method for the prediction of energy load. The developed RNN method has been compared with the CNN and ANN in the term of MAPE. Based on results, the RNN-based method provided the best prediction performance. Rahman et al. (Rahman and Smith, 2018) developed the RNN method in comparison with the ANN technique for the prediction of energy demand in commercial buildings. Evaluations and comparison have been conducted using the RMSE. The RNN provided much better accuracy than the ANN technique. In another study, Rahman et al. (2018) developed the RNN method for the prediction of BE consumption. The developed method has been compared with ANN in terms of accuracy and robustness. As a result, the RNN could improve the estimation better than the ANN method. Koschwitz et al. (2018) developed the RBF-based SVM and nonlinear autoregressive exogenous RNN for forecasting the BE load. The historical data have been employed from residential buildings in Germany in order to develop the target methods. Based on results, NARX-RNN could successfully improve the prediction performance compared with those of the SVM technique. In another study, Cai et al. (2019) developed a comparative study for forecasting the energy load in the building sector. The developed methods were the RNN and CNN. Results have been evaluated by accuracy and processing time. CNN could improve the accuracy and the reduction of processing time in comparison with the RNN method.

Long Short-Term Memory-Based Studies

LSTM can be considered as a subset of the RNN method which is used as a general purpose computer by employing the feedback connections. The applications of LSTM are sequences and pattern recognition and image processing. The architecture of LSTM contains the input gate, output gate and forget gate. **Supplementary Figure S10** presents the architecture of the LSTM method. Additional explanations about the RNN method have been presented in our previous study entitled the "list of DL techniques" (Ref. deep learning). Wang et al. (2019a) proposed the LSTM technique for the estimation of the BE load in comparison with LR and ANN methods. Findings have been analyzed using the RMSE performance index. LSTM could significantly increase the prediction performance compared with LR (about 40%) and ANN (about 23.7%). Matsukawa et al. (2019) explored a study for the estimation of energy consumption in air conditioner systems using LSTM methods. Using LSTM could successfully improve the prediction accuracy by up to 21%. In another study, Singaravel et al. (2018) developed single-, two-, and three-layered LSTM method for forecasting BE demand factors. The developed methods have been compared with the ANN in terms of accuracy and R2 values. DL techniques have been introduced to play effective roles in decreasing the processing time and enhancing the accuracy and robustness by increasing the prediction sustainability. As a result, DL techniques could successfully cope with the estimation, and the best prediction performance has been owned by the two-layered LSTM method. Laib et al. (2019) proposed the LSTM technique for forecasting gas consumption in the building sector. Prediction results have been compared with the ANN in terms of

RMSE, MAE, and MAPE. Results claim that LSTM improved the prediction results about 10–15%. Wang et al. (2019b) developed LSTM methodology for the estimation of energy load with an aim of controlling an HVAC system. Results have been analyzed by the RMSE method. LSTM could successfully cope with the defined task.

Ruiz et al. (2019) provided an exploration for the estimation of BE consumption. The developed methods were LSTM, ELMAN, and NARX methods. Findings have been analyzed using RMSE values. Accordingly, LSTM could generate accurate output values and provided the highest robustness. In another study, Jain et al. (2020) proposed a comparative study for the prediction of electricity demand in the building sector using XGBoost, ARIMA, LSTM, and ANN. Evaluations and comparisons have been performed using MAPE and RMSE factors. Based on results, XGBoost followed by LSTM provided the highest prediction performance compared with the ARIMA and ANN. Almalaq and Zhang (2019) developed a novel technique for the estimation of BE consumption using LSTM and GA methods to obtain an evolutionary DL method. The database related to residential and commercial buildings has been employed to evaluate results. Comparison has been performed using RMSE and MAE factors. As a result, the developed hybrid technique which takes an evolutionary DL method improved the prediction accuracy with a high sustainability for energy consumption over the common DL methods.

Convolutional Neural Network-Based Studies

The CNN can be considered as one of the most popular DL methods. This architecture of the DL method generally handles image processing applications. CNN has three layers called convolutional, pooling, and fully connected layers. In each CNN, there are two stages for training process: the feed-forward stage and the back-propagation stage. **Supplementary Figure S11** presents the architecture of the CNN technique. Additional explanations about the RNN method have been presented in our previous study entitled the “list of DL techniques” (Mosavi et al., 2019; Nosratabadi et al., 2019). Despotovic et al. (2019) developed an exploration for the estimation of heating demand in the building sector using the CNN technique. Findings have been conducted using accuracy and sensitivity factors. Accordingly, the developed technique could successfully estimate the heating demand with a high accuracy by 62% better than before. Zhou et al. (2019) developed a novel data-driven method using the CNN technique for the prediction of energy load in the building sector. Results have been evaluated using accuracy and reliability factors. As a result, the CNN could successfully cope with the forecasting task with a high accuracy and sustainability.

Results and Discussion

Supplementary Table S9 gives a brief evaluation about the accuracy, reliability, and sustainability of models developed for handling BE information using DL techniques. **Supplementary Figure S12** gives a concluded evaluation for each model based on their robustness. **Supplementary Figure S12** have been separated into four limitations containing high, good, medium, and low robustness scores to evaluate the capability and strength of each technique according to our observations and understandings from conclusion and findings of each study. According to **Supplementary Figure S12**, in general, DL-based techniques provided a higher robustness score. On the other hand, ensemble- and hybrid-based models provided a good robustness score, but ANN- and SVM-based models provided a medium robustness score. LR had the lowest robustness score.

DISCUSSIONS

According to the results discussed in the previous section, forecasting can be considered as the major application for the use of ML-based techniques. **Supplementary Figure S13** presents the trend and allocations of each application. According to **Supplementary Figure S13**, it can be claimed that the main trend follows forecasting in the BE sector. As it is known, the application of AI in the fields related to the building industry is increasing so that this increase is significant in the field of forecasting and estimation. As can be deduced from **Supplementary Figure S13**, most applications are related to forecasting, optimization, and clustering because these applications can be the key to entering the field of monitoring, building management, and developing intelligent security systems. On the other hand, they can also make tremendous progress in the field of smart buildings. One of the main criteria that can be discussed in this study is the issue of energy in the building. As shown in **Supplementary Figure S14**, the allocation of each of the models used in the topic of energy.

As is clear from **Supplementary Figure S14**, LSTM followed by the ANN and CNN has the highest allocation in BE sectors. LSTM and ANN have been employed for forecasting the energy load, energy consumption, and energy demand, and the CNN has been employed for forecasting the energy demand and energy load. The use of each model for a specific application has some advantages and disadvantages. **Supplementary Table S10** presents the advantages and disadvantages of each model for forecasting applications in the BE sector. According to **Supplementary Table S10**, it can be particularly concluded that using the DL and ensemble techniques can be successful in case of long-term records with an extra degree of freedom which includes a huge volume of data. But in case of a small volume of dataset or short-term predictions, single ML-techniques such as ANN, SVM, or hybrid ML techniques can be effective for taking a proper modeling performance in a limited process time. The amount of energy available in a building is usually directly related to the amount of comfort of its occupants. At the same time, it is also related to various categories such as environmental pollution, the volume of energy reserves at our disposal, and the costs of consumption in the form of energy. Prediction, forecasting, and estimation in the BE sector with the approach of optimization, management, and monitoring of energy availability in various applications can be considered the point of compromise between the comfort of the building and other categories and concerns of the economic field and the environmental sustainability. The output of this study can be important from two points of view: the first is to identify weaknesses and resource management in order to move towards smart energy consumption, which can be a subset of smart buildings, and the second is to focus on smart net-zero energy or smart low-net energy buildings. In today's world, due to the scarcity of energy resources, the importance of optimal energy consumption has become more and more important. An intelligent structure is a structure consisting of various control systems in which the activities and interactions of objects are completely intelligently managed. Therefore, a comprehensive management system and intelligent building by linking all sub-systems of the building, which unites and monitors different parts of the buildings to optimize energy consumption, improve efficiency and productivity devices, create value increases in the building, and increases the level of comfort in the building. In this regard, the role of the Internet of Things can be more significant. Although it can be claimed that smart energy systems in the building sector are costly, the cost of this system is offset by saving energy consumption and reducing service and maintenance costs.

Smart energy systems in a building are generally defined in terms of information and communication. For example, the amount of ambient light to determine the number of lamps needed to provide lighting requires sensors to measure the ambient light, a system that calculates the number of lamps required, a steering system, and a communication system to communicate between the components. The general basis for this connection in the computer world is data networks such as the Internet. Therefore, in order to achieve a large information system that includes other information such as the temperature in addition to lighting data, objects work together in data networks. This interaction between objects in a computer is called the Internet of Things. Based on this, objects send and receive information with the help of predefined identifiers in the heart of Internet protocols and are in relation to the information of other objects. This information communication of objects, which is called the Internet of Things, is performed through smart devices such as mobile phones. The importance of a smart energy system is also important from other aspects. In any case, energy resources are limited, and providing smart solutions for their optimal use can guarantee a better future. Depending on the texture and pattern of the city, there are numerous renewable energy sources available such as the solar and wind energy or non-renewable sources such as electricity coming from a power plant with fuel. Smart energy systems can be considered in the form of confronting the mentioned limitations in order to increase the level of satisfaction and at the same time reduce the cost. For example, the existence of smart curtains to deal with the sun and its effect on reducing the temperature of the building in summer or vice versa, using it to deal with winter cold along with other factors such as the amount of light required by the building, can be an example of the category Be. This level of intelligence, in addition to preventing energy waste, can increase the level of satisfaction and increase the life of construction equipment, reduce the time required for service, and reduce energy costs. Therefore, it is considered part of the principles of building engineering. It is necessary to explain that intelligence is not necessarily based on electronic and computer equipment, and the implementation of intelligent plans in building construction or intelligent selection of building equipment and facilities can also be discussed and accepted as intelligence. Future studies are moving toward the use of the Internet of Things in the smart energy systems in the building sector where advanced machine learning methods are used (Chen et al., 2020; Yanan Zhang et al., 2021; Hu et al., 2021; Zhao et al., 2021). The recent developments in this area big data and machine learning have motivated methods that can process stochastic problems in energy sectors. For instance, the methods (Shan et al., 2021; Tu et al., 2021) due to the higher performance would be a good candidate for building energy research.

CONCLUSION

This study explores the usage of ML-based techniques in BE information applications. The ensemble and hybrid techniques have emerged and continue to advance for higher accuracy and better performance. DL-based techniques also will bring tremendous amount of intelligence for improving the prediction techniques. The following findings can be concluded. For energy demand forecasting, hybrid and ensemble methods are located in the high robustness range, SVM-based methods are located in good robustness limitation, ANN-based methods are located in medium robustness limitation, and linear regression models are located in low robustness limitations. For energy consumption forecasting, DL-based, hybrid, and ensemble-based models provided the highest robustness score. ANN, SVM, and single Ml-based models provided the good and medium robustness, and LR-based models provided the lower robustness score. For energy load forecasting, LR-based models provided the lower robustness score. The hybrid and ensemble-based models provided a higher robustness score. The DL-based and SVM-based techniques provided a good robustness score, and ANN-based techniques provided a medium robustness score. In general, DL-based techniques provided a higher robustness score. On the other hand, ensemble and hybrid-based models provided a good robustness score, but ANN and SVM-based models provided a medium robustness score. LR had the lowest robustness score. The importance of a smart energy system is also important from other aspects. In any case, energy resources are limited, and providing smart solutions for their optimal use can guarantee a better future. Depending on the texture and pattern of the city, there are numerous renewable energy sources available such as solar and wind energy or non-renewable sources such as electricity coming from a power plant with fuel. Future studies are moving toward the use of the Internet of Things in the smart energy systems in the building sector. On the other hand, due to advances in ML-based techniques, there is still a computational cost due to the high complexity of data in building optimization and energy management problems, including multistage and nonlinear behavior of building thermal performance and discontinuity in optimization variables. Uncertainty in building processes and design parameters is a major barrier to the widespread use of soft computing. Future studies should focus on developing new methods and efficient solutions based on DL and ensemble methods and using them realistically on optimization studies and evaluating their performance and tools. The energy management sector in the building, according to the volume of data obtained and also its impact on energy consumption, energy load, and energy demand, as the core of energy, is the main goal of future studies.

AUTHOR CONTRIBUTIONS

Conceptualization, AM; methodology, AS and AM; investigation, LA; software, AS; formal analysis, AS and AM; writing—original draft preparation, AS; visualization, AS, LA, and AM; supervision, CM, BT, and AM; editing and revisions, AM, BT, and CM. All authors have read and agreed to the published version of the manuscript.

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SUPPLEMENTARY MATERIAL

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

GLOSSARY

ANN Artificial neural network
ANFIS Adaptive neuro fuzzy inference system
ANP Analytic network process
ARIMA Autoregressive integrated moving average
BE Building energy
ELM Extreme learning machine
DT Decision tree
SVM Support vector machine
WNN Wavelet neural networks
SVR Support vector regression
GA Genetic algorithm
MLP Multi-layered perceptron
LSTM Long short-term memory
ML Machine learning
RSM Response surface methodology
BPNN Backpropagation neural network
LS Least-squares
SB Sparse Bayesian
GBR Generalized boosted regression
GPR Gaussian process regression
RNN Recurrent neural networksRecurrent neural network
GBRT gradient boosted regression trees
ABC Artificial bee colony
CART Classification and regression tree
CNN Convolutional neural network
FFNN Feedforward neural networks
PSO Particle swarm optimization
RF Random forest
CM Centroid mean
DL Deep learning
NRTL Non-random two-liquid
RNN Recurrent neural networksRecurrent neural network
PLS Partial least squares
DA Discriminant analysis
PCA Principal component analysis
LDA Linear discriminant analysis
RBF Radial basis function
ERT Extremely randomized trees
MAPE Mean absolute percentage error
MCDM Multi criteria decision-making
GP Genetic programming
MLR Multilinear regression
SWARA Step-wise weight assessment ratio analysis
MOORA Multi Objective Optimization by Ratio Analysis
NARX Nonlinear autoregressive exogenous
HFMCD Hierarchical fuzzy multiple-criteria decision-making
SARIMA Seasonal autoregressive integrated moving average
R2 Determination coefficient
MAE Mean absolute error
RMSE Root mean square error.