Smart buildings Cooling and Heating Load Forecasting Models: Review

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Abstract
The proper implementation of the building cooling and heating load prediction models is a key factor to enhance the energy efficiency buildings usage. In the recent years, a number of researches conducted to forecast the cooling and heating loads. Most challenging and significant parts of prediction are determining the most efficient input parameters and develop a high accuracy prediction models. Several data-driven prediction models are proposed to develop the best control of the energy consumption systems, while provide a suitable indoor comfort environment. Despite of the number of review articles discussed the advantage and disadvantages of prediction models, there are gaps in reviewing cooling and heating load prediction models. This study provides a critical review of recent models used in cooling and heating load prediction by focusing on model performance and accuracy. The comparative analysis of the review shows that each prediction model has particular advantages in comparison to other models. Additionally, the review comes out with that most of the models has shortcomings from the parameters considered as input, and the techniques used to implement the models. The aim of this review is to highlight the disadvantages of existing models used in the cooling and heating load predictions and provide a comparative analysis of these techniques.
Keywords:
Cooling load prediction, heating load prediction , HVAC systems, Artificial Neural network, Support vector machine, Deep learning, regression analaysis.

1. Introduction

The study of energy required for the smart building became very interesting because the buildings considered as one of the largest sources consuming the power as well as the increment concern the world about energy sustainability [1]. This led the researchers to focus on energy management during the building's design stages and make buildings smarter by utilizing an Intelligent Control Systems (ICS). ICS uses the sensors devices to capture data before interpreted and handled by using rules and intelligent techniques to forecast the energy requirement. The main function of building control systems is to monitor the heating, ventilation and air-conditioning (HVAC) systems [2] and reduce waste of energy. HVAC energy prediction is an important issue to make the decisions to plan the future energy usage [3]. Additionally, the accuracy of the energy demand prediction applications is an important factor which reduces the costs of operations and prevents the systems from unexpected power blackouts [4]. To handle the problems of complexity in energy systems and forecasting the future load, several statistical and Artificial Intelligence (AI) models proposed such as Support Vector Machine (SVM) ,Artificial Neural Network (ANN), deep learning algorithm , linear regression models and ensemble models. Li and Wen [5] classified the predicting models in three types': physics-based models, hybrid models and data-driven models. The physical models rely on the physics concepts and equations to model the buildings components such as power consumption, outdoor and indoor attributes. The parameters for model components such as building structure, weather condition should be taken always from design plan and manufacture catalog. Secondly, Hybrid models benefit from the simple physical attributes of building to simulate the behavior of the power systems of buildings. However, it's difficult to obtain the parameters if the material and geometry of the building are not available. Thirdly, the data-driven model which finds the correlation among operation data power consumption of buildings. The model uses data measured during specific periods to train the data-driven models to be able to forecast the future power demand.

These models focus on improving the building energy efficiency by improving the prediction algorithms that will obtain high forecast accuracy and implement optimum optimizations algorithms [6]. The building's cooling and heating loads prediction become under consideration for researchers to predict optimum models and methods which increase buildings energy efficiency and protect the green environment [5]. The prediction models affected by the building parameters such as occupancy behavior, building's walls, windows, floors, roofs, ceilings, and thermal properties as well as the weather condition such as temperature, humidity[7]. Aforementioned issues make developing accurate and effective cooling and heating prediction techniques a challenging task. Consequently, studying the prediction techniques used in buildings cooling and heating are very important to provide a deep insight for researchers for the current state of cooling and heating systems [8].

Several review articles have been published so far on modeling cooling and heating load prediction in smart buildings. Das, et al. [1] studied the usage of the AI techniques to implement cooling and heating load prediction for buildings. However, authors discuss a few numbers of papers and not recently published. Afroz, et al. [2] categorized and presented a critical survey of modeling techniques used in HVAC systems. The review identified the strengths and weaknesses of different modeling methods and the deficiency of some models. A critical review for researchers' for 30 year that utilized the Artificial Neural Network in building energy analysis was reported by Mohandes, et al. [3]. A review of major supervisory control models and optimization algorithms used in HVAC systems was presented by Wang and Ma [4]. Afram and Janabi-Sharifi [5] concerned with the theory and applications of model predictive control for HVAC to review the control models. Kumar, et al. [6] reported a review of particular

Manuscript received December 5, 2020
Manuscript revised December 20, 2020
https://doi.org/10.22937/IJCSNS.2020.20.12.9

predictive control strategies use ANN techniques to optimize the thermal comfort as well as reduce the power demand.

In spite of the efforts provided by researchers to review and analyze these techniques and algorithms, there is still a lack of highlighting on cooling and heating load forecasting models. Moreover, there is a demand to clarify the strengths and weaknesses of the several modeling techniques which used in HVAC system to progress in research on modeling of HVAC systems components and operating conditions. The aim of this paper is to narrow the gaps by reviewing and analyzing the recent AI and conventional models that proposed to handle the cooling load and heating load prediction for smart buildings.

The paper was organized as explained in the following statements. Section 2 discusses in detail the previous works and explains the significance of this review. The research methodology used in this research demonstrated in section 3. The challenges and issues that faced the cooling and heating forecasting models accuracy and efficiency discussed in section 4. The cooling and heating load prediction models and techniques are reviewed in details in Section5. The paper concluded with elaborate of the open issues and challenges that need more research in the area. Additionally, the conclusion of the research which highlights the main point discussed in paper, are given in the final Section.

2. The review methodology:

The focus of this article is to review and analyze of the cooling and heating load prediction models and techniques that are used in the smart buildings. This comprehensive review includes only the research published between years 2010 and 2020. The study applies a review approach that contains three main steps; data collection, data analysis, and challenges and future works. The methodology illustrated in Figure (Fig 1).

1. The first step used to collect all articles related to the prediction of cooling and heating load in smart buildings. This step composed from following phase

- Determine the keywords that are related to the scope of this study, such as (cooling load, heating load, HVAC model, prediction, forecasting, Artificial Intelligence, Neural network, Support Vector machine, etc). These keywords are used as a single keyword or combination of keywords.
- Determine the data source that will use in searching for article published in the peer-reviewed journal and conference .this steps produced 5 most famous online databases as list below:
  - ScienceDirect (www.sceincedirect.com/)
  - IEEE Xplore (www.ieeexplore.ieee.org/Xplore/)
  - ACM Digital Library (www.portal.acm.org/)
  - SpringerLink (www.springerlink.com/)
  - Scopus (http://www.scopus.com)
  - Google Scholar (https://scholar.google.com)

  Additionally, for each article obtained from the search steps the authors check the reference part and include the relevant article in the review.
- Applying filter for the selection paper to refine the results based on several criteria such as the year of publication, content information, and keywords related to study.

2. The collected articles from previous steps studied and analyzed which produced a classification for all papers included in the review. The analysis comes out with a table that summarizes the main features and issues discussed in the reviewed articles.
3. The analysis table highlights the gaps of the previous research conducted in forecasting the cooling and heating load in smart buildings. Finally, the critical discussion focuses on open issues and challenges that faced prediction models are explained.

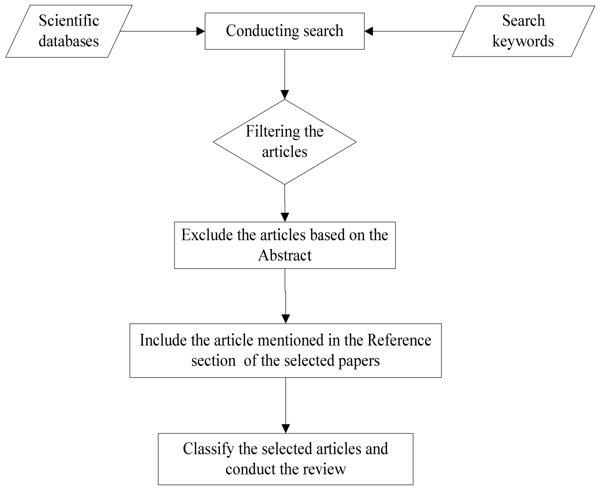

Fig 1: The research methodology.

3. Problems facing the cooling/heating load prediction models:

Cooling and heating prediction is an important technology for ensuring the energy consumption in the future. The techniques and models of cooling and heating load prediction in smart buildings are studied by a good number of researchers by implementing AI and Machine Learning (ML) algorithms. The proposed techniques vary in obtaining accurate and good results, due to the several factors that faced the researchers related to buildings attributes, weather condition and the data produced by the control systems themselves. The following are the most significant issues that increase the difficulty in relation to the accuracy of load prediction:

1. The building attributes have a large number of detailed information that is needed by the predicting models, which may not be easy to measure and compute [7].
2. The difficulty of describing the function that relates to the previously mentioned issue and both the cooling and heating load because it is common linear regression[8]. Additionally, the building systems nature is extremely non-linear which makes the relationship more complex.
3. Activities and behavior of the occupant inside the building is predictable because the occupants' behavior don't have a fixed pattern but change with irregular manner.
4. The simulation tools such as Energy Plus[9] and ESP-r[10], that have been used by building load forecasting models obtain accurate load prediction in many applications[11]. However, trying to use different simulation tools for the same dataset and models produced diverse results.

The aforementioned challenges lead the researchers to propose a number of models to predict the cooling and heating load in smart buildings.

4. The review and analysis of the Cooling and heating load prediction models:

The data-driven models used for estimating both the cooling and heating load are relied on the building data and weather data to find the relevant variables and develop appropriate models. Recent researches used advanced data-driven models such as ANN and ML to enhance the efficiency and prediction accuracy. The prediction accuracy depends on the techniques used to develop the prediction model and the feature used as input to the models. Due to the fact that data-driven features, flexibility, and advantages there are numerous researches conducted in this topic which achieve great results; however, some gaps still need to be filled. This study tries to highlight the models and techniques used for the cooling and heating load estimation in buildings. The review and analysis-as explained in the sections below- classify the models into four categories ANN, deep learning, SVM, and analysis regressions. The Figure (Fig 2) illustrates the number of the papers reviewed in each class.

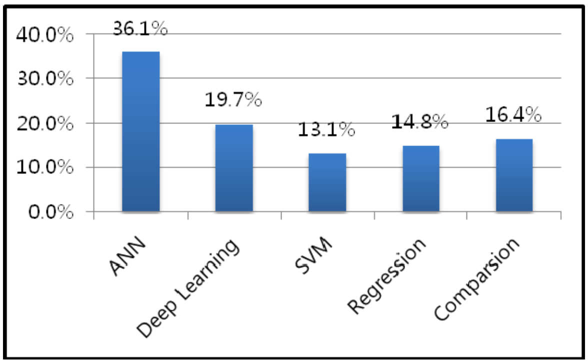

Fig 2. The ratio of the reviewed paper based on the classification

4.1. Artificial neural networks

Artificial Neural Network is simulating the human brain neuron networks concepts to build computational networks to solve complex problems[12]. The complexity came from attributes of these problems such as nonlinear, several different variables, and not well defined problems. The structure of ANN is similar to the human nervous system which the neurons represent as processing elements with similar attributes such as input, synaptic, and output [13]. The structure of ANN –as explain in Figure (Fig 3)- is represented in three layers: input layer, hidden layer, and output layer in which the connection between neurons holds the network's weights. The ability of ANN to model the cooling and heating loads for dependent or independents, lead researchers to use it to forecast the cooling and heating loads.

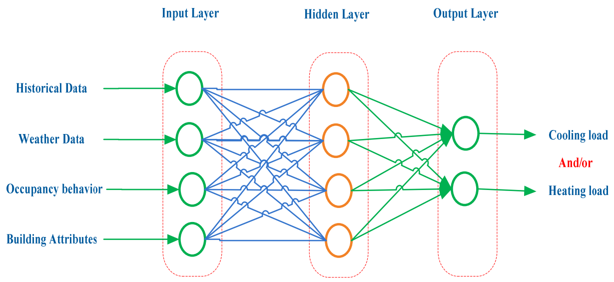

Fig 3. The typical ANN architecture for predicting cooling/heating load

Several studies conducted to predict the heating load using the ANN models. Sandberg, et al. [14] developed the district heat load prediction model by using Nonlinear Autoregressive Neural Networks with External Input (NARX). The results show that the selected input for an hourly basis (13 input) affects the accuracy of the model which obtained 96% of the accuracy. In addition, the study revealed that the electric metering system is limited by the current district heat measuring system data resolution. Jovanović, et al. [15] examined the usage of network ensemble to maximize the precise of the heat load prediction. This is conducted by implementing three NN named techniques Feed Forward Backpropagation Neural Network (FFNN), Radial Basis Function Network (RBFN), and Adaptive Neuro-Fuzzy Inference System (ANFIS). Furthermore, to improve the accuracy of heat load prediction a more three ensemble model developed by using the FFNN, RBFN, and ANFIS techniques. Sajjadi, et al. [16] developed multi-step ELM based models for predicting the consumers' heat load in DHS. The experiments illustrated that ELM models improved the prediction accuracy and generalization capability when compared with GP and ANN. Furthermore, the ELM models obtain, in large number of cases, a good generalization performance and have an ability to learn fast in comparison to conventional algorithms.

On the other hand the ANN used also to expect both the cooling and heating load. Chou and Bui [17] propose and implement ensemble model which higher the load estimation accuracy and help the early building design for load maintenance. The study started by evaluating the performance of Support Vector Regression (SVR), ANN, classification and regression tree (CART), chi-squared automatic interaction detector (CHAID) and general linear regression (GLR) to build an ensemble model for cooling and heating load prediction. The evaluation comes out with two techniques SVR+ANN for cooling load prediction and SVR for heating load prediction. Furthermore, the single and ensemble models can be applied only to the 12 building types specified in the study. Sala-Cardoso, et al. [18] hybridization the activity indicator and power demand models to develop HVAC power demand prediction model. Recurrent Neural Networks (RNN) used to build the activity indicator and to improve the patterns temporal dynamicity as well as context awareness. On the other hand, ANFIS is used to build the power demand model. At last, the integration of both models produces a robust and reliable prediction model. The experiments illustrate that the proposed model offers good performance. What is more, when using the activity as an additional parameter, the error is decreased significantly. Luo, et al. [19] proposed a day-ahead estimating model based on machine learning for building cooling and heating demand. The proposed model is composed from 4 layers of IoT based big data platform which is the main part contains the hybrids ANN and k-means clustering models. The k-means algorithm is used to identify the daily outdoor weather profile based on their attributes and then categorizes the profile -for all year- into featured groups. The ANN trained by using the groups produced by k-means, reading data from sensors, and cooling and heating building schedules.Zhou, et al. [20] used Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) to optimize the Multi-Layer Perceptron (MLP) neural network to estimate the cooling and heating load for residential buildings. The studies used a trial and error technique to decide the best parameters of the MLP, ABC-MLP and PSO-MLP networks. The experiments show that the utilization of the ABC and PSO algorithms enhanced the efficiency of the MLP.

Moreover, the PSO outperforms the ABC in terms of improving the MLP. Kumar, et al. [21] utilized the attributes of the building structure such as glazing area, roof area, and surface area to develop an Online Sequential Extreme Learning Machine (OSELM) based on an online/real-time prediction model for cooling and heating load. They used diverse feature sets and activation functions to develop 12 models based on OSELM and 12 based on ELM models. The results demonstrated that the OSELM and ELM based models outperform the ANN, SVM, RBFN, and RF in terms of generalization, efficiency, and error reduction. Chaowen and Dong [22] developed a dynamic cooling forecasting model based on BPNN for large buildings with ice-storage systems. The BPNN model used Bayesian Regulation Algorithm (BRA) to enhance the generalization ability of the NN. The experiments illustrated that the model is able to accurately predicate the future hourly load of the 1 week and 1 day with small error from the actual load. The result proves that the BPNN is able to predict accurate load even if the building information is reduced. Wang, et al. [23] integrated the ANN with an ensemble method to develop a dynamic building cooling load prediction model based on physical concepts rather than recorded data. Two prediction models A and B proposed based on Radiant Time Series (RTS) and Fourier's law methods. The result shows that the ensemble model combining model A and B obtain a high accuracy rather than use each model separately. A Time Series and NNs model proposed by Zhuang, et al. [24] to predict cooling load that use Ice Thermal Energy Storage technology by taking into account the tendency characteristics and periodical of the building load. The Autoregressive Integrated Moving Average (ARIMA) used to describe the linearity and periodicity of load while BPNN used to describe the residual error. The paper consider a 10 hour load time because the short-term does not useful for the ice charging process. The result shows that the proposed model outperforms ARIMA and obtains the highest accuracy for longer time. A new forecasting methodology is presented by Deb, et al. [25] to develop an institutional building cooling load prediction model using FFNN model with BRA. The energy consumption data is classified into classes to decrease the degree of variation. The authors found that dividing the data to five classes is most appropriated to obtain accurate prediction load and for condensing the high variability. Additionally, the ANN has an ability to estimate the upcoming day load accurately based on the five previous days' load. Shamshirband, et al. [26] apply the ANFIS to enhance on-line heating load model for individual consumers in District Heating Systems (DHS). The ANFIS model uses sensitivity analysis method to select the most input significant parameters. The obtained results prove that ANFIS is able to deal with the uncertainties in the model as well as it is capable to learn and predict the heating load. Zhang, et al. [27] proposed ANN-based model to predict the Ultra-short-term building cooling loads while the uncertainties quantity was described by developing a generic prediction interval estimation method. Moreover, the similar operating condition of historical prediction residuals is gathered by developing a Chebyshev distance-based agglomerative hierarchical clustering approach. The results show that the prediction value is close to the actual energy consumption value. Furthermore, the predictions residual is affected by their distribution over diverse clusters which leads to obtain different value. The Gradient Boosting machines performance was evaluated by Goliatt, et al. [28] to predict the cooling and heating load for residential buildings. The proposed model use the grid search algorithm to select the input parameters while the cross validation used to train the parameters. The GB model obtains highest performance accuracy when compared with SVM and Random Forest models.Guo, et al. [29] studied the effect of different seven input parameters in developing the heating load prediction model. The study implements four ML techniques include Extreme Learning Machine (ELM), BPNN, and SVR and MLR models. The feature parameters are optimized using correlation analysis and Least Absolute Shrinkage and Selection Operator methods. The results show that ELM outperform the other machine learning and obtain a better performance even when the number of features decreases.

Wu, et al. [30] studies the usage of Vortex Search Algorithms (VSA) and Backtracking Search Algorithm (BSA) in enhancing the performance of the MLP model to predict the residential building heating load. The experiment approved that the MLP model that optimized by VSA obtain highest accuracy when compared with the BSA-MLP and BP-MLP models. The result showed clearly that using the VSA and BSA methods enhances the performance of the MLP model in predicting the heating load. Moradzadeh, et al. [31] proposed MLP and SVR models to estimate both loads of the cooling and heating in residential buildings. The study enhance the model accuracy by initiate a linear mapping between the input and output parameters. The results show that the MLP obtain higher prediction accuracy for heating load, while the SVR achieved the best prediction accuracy for cooling load.Panyafong, et al. [32] developed an ANN model to predict the heat load that aims to reduce the power consumption and peak demand. The sensitivity analysis selected three factors- Tamb, Troom, and Gsolar- as a main input parameters which have highest affect on heat load model. The model reach its optimality in terms of performance by using the "Tansig" as transfer function of the output layer and tansig and logsig as transfer function for hidden layers. The study found that the increment of the neurons number enhanced the ANN performance. However, it is not proven that the increment in the hidden layer can improve the model performance. Moayedi, et al. [33] implemented MLP model to predicts the building cooling load while optimizing the MLP relying on Elephant Herding Optimization technique. The authors used Ant Colony optimization (ACO) and Harris Hawks Optimization (HHO) algorithms as benchmark models. The ensemble EHO and MLP enhance the neural weights and biases of the MLP. The results revealed that the EHO-MLP outperforms the other two models (ACO-MLP) and (HHO-MLP) in term of training and testing accuracy. Li, et al. [34] use the ANN recommendation system to develop a meta-learning strategy named "Walking slide method" to predict factory building cooling load. The proposed strategy predict the cooling load in real-time while utilizing the user preference. The experiments conducted using 40 cases for prediction by using six regression models and employed the two-stage user preferences method. The authors found that the SARIMAX and RF obtain the best prediction accuracy for major cases, while the LSTM offer higher accuracy when using the two criteria. The usage of meat-learning strategy enhances the ANN-based systems and improves the generalization.Bünning, et al. [35] handled the ANN high variance problem by introduces two correction methods, based on the online learning and error autocorrelation. The developed models are used to predict the heating load for complex building and districts with individual usage and occupant. The findings show that the correction method enhances prediction accuracy and decrease the variance in prediction performance. In addition, the ANN with correction methods obtains higher accuracy in comparison with other grey-box and black-box prediction models.

ANN models are able to handling the complicity and non-linear systems such as the cooling/heating energy consumption prediction. The review stated that ANN models as in [14-35] can obtain higher accuracy with contrast with other models. Nevertheless, building the ANN model is required to determine an important controlling parameters in spite of the fact that the ANN suffer from generalization capability [36]. Additionally, most of the studies have not taken into account the relative humidity and the indoor temperature as input parameters which have a negative effect on the accuracy of the ANN models. What is more, the occupancy behavior is not considered as an input parameter in the majority studies.

4.2. Deep Learning

Deep learning (DL) concept is defined by LeCun, et al. [37] as a method that permits computational models with several processing layers to learn data representation with several levels of abstractions. DL is similar to artificial neuron networks architecture, but DL can be implemented using multiple hidden layers and for every layer can have different functions. Additionally, the DL can be classified into a supervised prediction model to implement a Deep Neural Network (DNN) model or unsupervised feature extraction technique to implement a Deep Auto-Encoder (DAE) model.

In recent years, the DL utilized by several researches as model to predict load of the HVAC systems.. Roy, et al. [38] developed the DNN model to estimate both cooling and heating demand for indoor environment. The DNN uses a hierarchical framework that extracts the nonlinear information in several steps. The proposed model compared with GBM, GPR, and MPMR models. The result shows that the overall performance of GPR and MPMR models is higher in comparison to the other two models. However, DNN and GPR obtained an optimum predicted VAF among other models. Song, et al. [39] integrate parallel features of Convolutional Neural Network (CNN) and ability of handling time series features of RNN to develop a Temporal Convolutional Neural network (TCN) based algorithm. The TCN is an algorithm to predict the heating load of DHS that enhance the forecasting accuracy by using the grid search algorithm to optimize the NN's hyper parameters. The results show that the proposed algorithm obtains better results when compared with several other models. What is more, the algorithm obtains significant prediction accuracy if it is utilized in order to forecast for diverse time length. Liu, et al. [40] developed strand-based Long Short Term Memory (LSTM) recurrent neural network models that forecast a real time heat load for buildings. The proposed model enhances the robustness and the generalization by ensemble the LSTM units with a diverse initialization in parallel. Following that, the prediction of DHS load computes by averaging the output from each network. Additionally, the model proposed two methods: smoothing and rescaling that were used in the pre-processing stage to reduce the accuracy errors. Dynamic Neural Network Models- or Time Delay Neural Network (TDNN) – developed by Sholahudin and Han [41] to forecast the instantaneous building hourly heating load based on several weather variables. The efficiency of the input variables to the model is tested by using the Taguchi method. The study has been done based on static and dynamic ANN models. The result illustrates that the TDNN obtained the best estimation accuracy in comparison to other static models. Furthermore, the accuracy enhanced at the beginning when the hidden neurons increased until it reaches the constant value. Fu [42] proposed a hybrid model composed from Empirical Mode Decomposition (EMD), Deep Belief Network (DBN) and ensemble technique to obtain a high accurate cooling load prediction. The hybrid model breakdown the data series to a number of components by using EMD, while DBN used to extracts from the cooling data the hidden invariant structure and nonlinear features. However, to reduce the effect of uncertainties of the model and the noise of data on prediction accuracy, the study implements an ensemble technique. The experiments show that the hybrid model provides a high stability and robustness as well as obtain a better result when compared with BPNN and SVM models. Fan, et al. [43] explored the usage of DL technique to implement a 24-h a head building cooling load models. The study proposed a supervised DL model to predict the cooling load, while proposed unsupervised DL model for features extraction to improve the model performance. The performance of the models tested by compare it with MLR, Elastic Net (ELN), Random Forests (RF), Gradient Boosting Machines (GBM), SVR, and Extreme Gradient Boosting Trees (XGB). The results show that the XGB model use unsupervised DL –DAE- for features extraction, obtained the best prediction accuracy. While the supervised DL do not obtain a good result to predict the cooling load. Rahman and Smith [44] investigated the utilization of Deep RNN in forecasting the commercial building heating load for medium to long term time horizon. The framework used the Bayesian optimization techniques to decrease the number of function evaluation for every given timestep while the Gaussian Process regression is used to evaluate the solutions to the Bayesian process for every timestep. The authors found that the deep RNN outperformance the 3-layerMLP and get better accuracy.

Deep reinforcement learning (DRL) algorithm, namely Deep Deterministic Policy Gradient (DDPG) is proposed by Liu, et al. [45] to predict the HVAC system control load. DDPG utilized Autoencoder (AE) to extract the most important features from raw dataset as well as it used to optimize the predictioin model to improve the model performance. The results illstrate that the DDPG and AE-DDPG outperfom the supervised models such as SVM and BPNN models and obtain high accuracy. The authors found that the DDPG model work better than other models when dealing with short-term energy consumption prediction. The SVR, DNN, and XGBoost models are adapted by Xue, et al. [46] as based learner to develop prediction's framework for multi-step ahead DHS load. The models applied in two strategies the direct and recursive to train the model to forecast daily heat load curves. The result shows that the XGBoost-based that used by the recursive strategy obtained the highest accuracy and stable prediction value. Sendra-Arranz and Gutiérrez [47] designed and implemented several models to estimate the HVAC next day load based on the previous day behavior to enhance the prediction accuracy. The study developed a three multi step prediction models based on stacking LSTM NN model while the RNN's unfolding methods used to understanding the temporal behavior. The models illustrate high performance results for the 24h ahead prediction, however, when the horizon is reduced to one hour the model also obtains good results A dynamic NARX is developed by.Katić, et al. [48] to predict the heating load and utilizes in controlling the personalized heating systems. The experiment conducted using two models for two subjects, model A obtained the best result when it used 12 hidden neurons while model B used 16 hidden neurons. The study approved that the NARX models can be able to provide a comfort personalized heating during the test period. Chen, et al. [49] introduced deep learning algorithms called Stacked Auto-Encoder (SAE) and a meta ensemble learning methods to develop cooling load prediction model for the commercial building. The SAE is utilized to study the deep features of the cooling load data while meta ensemble studied the nonlinear features and determine for SAE-based point forecaster their coefficients. The findings show that the proposed model outperforms the traditional BPNN, SVM, and WT+SVM algorithms.

The harnessing of the deep learning techniques in recent year is growing rapidly and makes them to be another option rather than conventional ANN models. Several supervised and unsupervised deep learning model was used to predict the cooling and heating load such as [38-49] obtain high accuracy. However, the experiments approved that the increment of the hidden layers (deeper) in the NN does not increase the model accuracy as reported by Koschwitz, et al. [50]. When the hidden layer number is increased, the accuracy start to improve until reached constant value. Furthermore, the deeper networks increase the computational cost, which it affects the model performance. On the other hand, the input parameters and number of tapped delays determined the problem complexity and affect in determine the optimal number of neurons.

4.3. Support Vectors machine

Support Vector Machine (SVM) developed to map nonlinearly data into highest dimensional feature space by using nonlinear mapping. The SVM is unsupervised, self-learning, and non-linearity similar to the NN. The SVM mapping low dimensional input space to high dimensional feature space by using kernel functions. The four kernel functions used by SVM are Radial Basis Function (RBF), sigmoid, linear, and polynomial functions, while the simplicity, reliability, and efficiency of RBF made it the best kernel function [51]. The SVM model obtains a high prediction accuracy based on the proper selecting of the model input parameters. The linear regression is described in the following equation.

$$f(X) = \left(w \cdot \Phi(X)\right) + b \text{ with } \Phi: R^n \rightarrow \Gamma, w \in \Gamma$$

Where the original data is represented by x, a higher dimensional feature space is Γ, a nonlinear mapping is Φ and b refers to the threshold. The SVM is used in several disciplines to predict processes such as energy consumption and HVAC systems load prediction.

The objective of the research in [52] is to study the feasibility and applicability of implementing SVM to forecast cooling load for HVAC systems. The performance is measured by using upper bound C and the kernel parameter δ^2 in the SVM using stepwise searching method based on RBF kernel. The result shows that the SVM obtained error around 4% when compared with the actual load. Ding, et al. [53] developed two cooling load prediction models for building offices: Genetic Algorithm -Wavelet decomposition-support vector regression (GA-WD-SVR) and Genetic Algorithm-support vector regression (GA-SVR). In proposed models, the parameters of the SVR function are optimized by using GA, while the cooling load sample uses WD to perform multi-frequency analysis. The experiments show that the performance of the GA-SVR models is better when applied for short-term cooling load prediction. While GA-WD-SVR is obtained the best result when used for ultra-short-term cooling loads prediction. Xuemei, et al. [54] investigated the ability to integrate Least Squares (LS) and SVR models to develop predicted building cooling load. The proposed model named LS-SVR is aimed to handle nonlinear regression and time series issues. PSO algorithm is applied to optimize the LS-SVR parameters due to the fact that the PSO needs a less memory and time as well as simple implementation and effectiveness. Al-Shammari, et al. [51] developed SVM-with Firefly Algorithm(SVM-FFA) model that predicted the consumers' heat load connected to the DHS. The SVM-FFA is a multistep-ahead model which is used for short-term and utilize FFA to optimize SVM parameters. The result shows that SVM-FFA obtains better accuracy than GP, ANN, and SVM with grid search algorithms. Furthermore, the findings conclude that in the dynamic models with using soft computing algorithms to predict the load are not suitable. Protić, et al. [55] proposed multi steps model for heat load forecasting for consumers that connected to DHS named SVM-WAVELET. The model used SVM to minimize the upper bound generalization error while Wavelet analysis used to decompose the time series of data to several elements to passed SVM model as parameters. The results show that the proposed model outperforms the ANN and GA models and enhanced prediction accuracy. Hybrid prediction model called Wavelet-PLS-SVM for dynamic cooling and heating load proposed by Zhao and Liu [56]. The features extraction performed by wavelet transform while the multicollinearity problems handled by PLS. The SVM is used to handle the nonlinear problems while the PSO is used to optimize the SVM parameters. The experiments illustrate that the Wavelet-PLS-SVM can achieve dynamic load prediction for diverse time horizons while keeping the accuracy high. Li and Meng [57] studied the utilization of the SVM and conventional ANN to predict the hourly buildings cooling load and applied to one office and library building. The experiments show that the SVM and ANN are able to predict effectively the hourly cooling load. Additionally, the SVM achieved a best accuracy and generalization when compared with ANN model. Moreover, the SVM is fast learning than ANN especially when the training dataset available is limited. Tao, et al. [58] handled the parameters selecting problem of the SVR model by developing a Modified Simulated Annealing (MSA) optimization technique by enhancing the disturbance range and the annealing plan. The robustness, low calculation consumption, and strong global optimization are the advantage of using MSA technique in MSA-SVR model. The results show that the MSA-SVR model outperforms the SA-SVR model and the VFSA-SVR model. Furthermore, the utilizing the MSA optimization significant enhanced the prediction accuracy and stability of the prediction model

The support vector machine or the support vector regression is utilized in developing building cooling or heating prediction models. Most SVM techniques developed are obtaining a higher accuracy in comparison to other data-driven models. However, the amount and the description of the training data affect the performance of prediction models due to that, determine the optimal size of training data and decide the most relevant models' parameter are significant issues. On the other hand, to identify the effect of uncertainties in the prediction model is important issue because he weather forecast data obtained from the weather service provider.

4.4. Regression Analysis Models

Regression analysis is statistical models that illustrate the variation of a dependent variable to explanatory variables used as input in the function [59]. The regression analysis uses the input data to find the best fitting model coefficients and to determine the suitable mathematical model. The statistical models include the multiple linear regression and multiple nonlinear regression methods which include Autoregressive (AR), Autoregressive with exogenous inputs (ARX), and Autoregressive moving Average (ARMA), Autoregressive moving Average exogenous (ARMAX), time indexed ARX, Multiple Linear Regression (MLR), and multiple nonlinear regression (MNR).

Huang, et al. [7] proposed a Bayesian Network Model (BNM) for cooling load predication commercial buildings. The aim of study is to find how the outdoor weather conditions and internal building activities affect the cooling load. The experiment shows that the BNM obtains the same accuracy when compared with a SVM model, and better than an ANN model. Furthermore, the researchers found that the accuracy of forecasting is affected by uncertainties in the weather forecast however the sensitivity of SVM for uncertainties is more than two other models. Fan and Ding [60] forecasted the cooling load in public buildings by using a MNR model. The proposed model used to forecast the next hour cooling load for large public buildings based on a reference day. MNR improves prediction accuracy by using the sensitivity analysis to choose the key variables. The results prove that the MNR model outperforms the traditional models. Qiang, et al. [61] developed a model to predict the daily mean cooling load for office buildings by improving the MLR models. The study enhances the prediction accuracy by utilizing Cumulative Effect of High Temperature (CEHT) as an input variable to model. The change of cooling load is corrected by proposing the dynamic two-step correction. Furthermore, the meteorological factors mainly correlated to the daily mean cooling demand is determined by integration of simple correlation analysis and partial correlation analysis. Fan, et al. [62] consider the regression models to implement office building cooling load prediction. The ARX is proposed based on traditional ARX and sensitivity analysis to select best input variables. Additionally, the model reduces the errors relying on least square method. Whereas the impact of system non-linearity is minimized relying on the quadratic terms. The results demonstrate that the model enhances the accuracy and it is able to adapt real applications for HVAC control systems. Fan, et al. [63] research focus on analyzing MLR, AR, ARX, MNR, and a BPNN models to improve the prediction accuracy. Additionally, based on the result of analysis, they propose MNR models for quickly building cooling prediction. The result proves that MNR is better than BP model as well as the regression models obtain better performance than BP model. Furthermore, when the training time scale increased, the author found that the prediction accuracy increased while decreasing for the regression models. Sarwar, et al. [64] integrated an indexed ARX model with real time predictive control methods to forecast hourly building thermal. The indexing means that the prediction equation used different coefficients based on diverse time intervals and temperature. The authors found that the ARX model is not only able to predict accurate cooling load within the uncertainty bounds of actual load, but also, the ARX has an ability to enhance and capture the cooling load profile when the real data is used to measure the coefficients. Fan, et al. [65] used an interaction terms and higher order to improve the traditional ARX model accuracy and develop improved cooling load forecasting model. The results show that improved ARX model achieve good prediction accuracy when it is compared with data produced from the EnergyPlus simulator for 5 cities in china. Moreover, the result show that the Improved ARX model has an ability to work in diverse climatic conditions zones. Guo, et al. [66] introduce a time-indexed ARX models to forecast the hourly cooling load for diverse forecasting periods. The two-stage weighted least squares regression is used to estimate the coefficients of prediction models and reduce the influence of outliers. The proposed models represent nonlinearity and inter-correlation between input parameters by including temperature and interaction terms. A case study proves that the time-indexed ARX outperforms both the ANN and ARX models and achieve highest accuracy.Dong and Lam [67] integrated cooling and heating buildings control by introducing a methodology that considers the local weather and the occupancy behavior. The aim of this model is to decrease the energy consumption and keep the indoor temperature based on continuous measured data. Following that, a real-time Nonlinear Model Predictive Control (NMPC) model was developed relying on dynamic programming. The results show that the model heating consumption reduced by 30.1% while the cooling energy consumption reduced by 17.8%.

Regression analysis models are simpler, can applied to any building types, not complicated, but less accurate when it is compared with the AI algorithms. What is more, the most of the multiple linear regression techniques are not able to adapt quickly to dynamic nonlinear when the time is changed [60]. This relay on the rate of dynamic linear changes happens and the size of data that used by regression. Furthermore, the type of the buildings affects the prediction model accuracy. For example, the wind in single building can be considered as input to regression models, while in large number of buildings the wind will ignored. Therefore, the input parameters for regression models should be selected properly with consideration to the most relevant.

4.5. Compare Models

The cooling and heating load prediction is a complicated process because of the nonlinearity features and affected by both weather parameters and building types. The data-driven models are proposed to handle mentioned issues and implement effective prediction models. Consequently, a number of researchers conducted a comparison study to find the best data-driven models to be used in cooling or heating load prediction. The comparison studies explained and discussed the following section.

Xuan, et al. [68] propose a study to compare the performance of four machine learning include Chaos-SVR, Hybrid Wavelet-SVR (WD-SVR), SVR and BP models to predict the air-conditioning cooling load in shopping malls.. The experiments illustrate that the Chaos-SVR and WD-SVR show superiority over the other two models while the algorithmic complexity increases. The study concludes that the best model for shopping mall cooling prediction is Chaos-SVR due to its characteristics. Gu, et al. [69] investigated a wavelet neural network (WNN), ELM, SVM and BPNN optimized by a genetic algorithm (GA-BP) models to predict the heat load for residential buildings. The study aims to provide the best accuracy prediction model based on how the indoor temperature affects the prediction model. The ELM and GA-BP were proved to obtain higher accuracy than WNN. Furthermore, The SVM obtains the robust and the best prediction accuracy rather than other NNs models. Ahmad, et al. [70] studied MLR, GPR, and Levenberg–Marquardt backpropagation neural network (LMB-NN) models to estimate the building cooling load demand. The aim of the study is to find a method to analyze the previous recorded usage energy and run medium- and long-term forecasting with DM models. The study concluded that the GPR is higher precise in terms of MAPE for short-term forecasting. Moreover, the LMB-NN model is not only the best accuracy in the medium term but also it is more suitable to handle least squares non-linear issues. Ahmad and Chen [71] investigated the performance of several DM models named- Tree Bagger (TB), GPR, Bagged Tree (BaggedT), NN, MLR, Boosted Tree (BoostedT) to predict the cooling and heating load of Water Source Heat Pump (WSHP) of an office building. The study proves that the accuracy of TB, BoostedT, GPR, NN and BaggedT are better than the MLR model. Furthermore, the proposed DM models obtain the similar prediction accuracy when compared with the BRNN model. Idowu, et al. [72] present a bottom-down method to analyze ML models which is applied to predict the heating load for district heating substations. SVM, FFNN, MLR and regression tree are the supervised ML techniques used in the study. The experiments are conducted using different forecasting horizons for each hour with a range from 1 to 48 h .Furthermore; the suitable models with lower performance error are SVM, FFNN, MLR and better than regression trees. Roy, et al. [73] explore ML models to forecast the cooling and heating load based on specific parameters, named, Multivariate Adaptive Regression Splines (MARS), ELM and a hybrid model of MARS and ELM. The findings show that the MARS obtain better performance, but it takes much processing power and computation time. Moreover, the hybrid model achieves better RMSE than MARS and ELM. Furthermore, the proposed models outperform the traditional models like linear regression, NN, Gaussian processes and RBFN. Afram and Janabi-Sharifi [74] compare the performance accuracy of the gray-box model with a number of black-box models include ANN, transfer function (TF), process, state-space (SS) and ARX that used in HVAC systems. The results show that all used models to predict the HVAC load were able to forecast the load in most situations accurately especially when using visual inspection. While the analytical metrics proves that the ANN obtain the best results followed by TF, and ARX and at last SS, process, and gray-box models. Koschwitz, et al. [50] studied the performance of SVM-R based on RBF, SVM-R based on polynomial kernel, NARX RN with one hidden layer, and NARX RN with several hidden layers which used to forecast the cooling and heating load in non-residential district. Based on the MAE and MSE the comparison results illustrate that the NARX RNNs show superiority over SVM-R models in terms of providing high accuracy. Additionally, the authors found that the increment of the hidden layers (deeper) in the NN does not increase the model accuracy.

Table 1: Comparison of the cooling and heating load prediction models

paper	**technique**	**Type of prediction**	**Type of building**	**prediction term**	**dataset**	**year**	**Simulation or real**	**Feature sele. Tech**	**comparison of forecasting results**	**Evaluation metrics**
[14]	NARX	Heating	commercial building	long-term	Historical + Weather	2017	MATLAB's	-	Actual load	MSNEP , R^2
[15]	FFNN, RBFN and ANFIS	Heating	University campus	short-term	Weather Historical	2015	Matlab sim	-	Actual load	R^2,RMSE MAPE
[16]	ELM	Heating	district	short-term	Historical	2016	Matlab	-	GP, ANNs	RMSE, r, R^2
[17]	SVR +ANN	H/C	Public buildings	short-term	experimental datasets	2014	Ecotect	-	ANN,SVR, CART, GLR CHAID,	RMSE, MAE, MAPE
[18]	RNN	Hvac	building	short-term	historical + occupancy data	2018	N/A	-	classical model based on ANFIS	RMSE, MAPE, MAE, MAX, R^2
[19]	*k*-means clustering+ ANN	Heating Cooling	building	short-ahead	Historical weather data	2019	Simulation	-	Simulation with TRNSYS	MAPE
[20]	MLP	Heating	residential	-	-	2020	MATLAB	-	ABC-MLP	R^2 ,MA

paper	technique	Type of prediction	Type of building	prediction term	dataset	year	Simulation or real	Feature sele. Tech	comparison of forecasting results	Evaluation metrics
	NN	Cooling	buildings						and PSO-MLP	E , RMSE
[21]	OSELM	Heating Cooling	buildings	short-term	historical	2018	-	-	ANN,SVM, RBFN, RF	MAE
[22]	BPNN	Cooling	business building	short-term	Historical +weather	2015	DeST	PCA	Actual load	RMSE
[23]	ANN with an ensemble	Cooling	office building	short-term	Historical +weather	2018	TRNSYS	RTS	Actual load	R^2
[24]	ARIMA+NN	cooling	office building	short-term	historical	2015	DeST	-	Actual load + ARIMA	-
[25]	ANN	Cooling	institutional buildings	Short-term	Historical weather	2016	Matlab	-	-	R^2
[26]	ANFIS	Heating	District	Short-term	Historical	2015	MATLAB	sensitivity analysis	Actual load	RMSE,R^2
[27]	ANN based model	cooling	office buildings	Ultra-short-term	Historical	2020	-	-	actual	MAE , RMSE , R^2 , CV-RMSE
[28]	GBM	Cooling heating	General building	-	historical	2019	-	exhaustive search with cross-validation	DT, MLP, RF, SVR , GP.	RMSE, MAE, MAPE, 1 - R^2
[29]	ELM	heating	Office building	Short-term	Historical weather	2018	-	correlation analysis ,LASSO	MLR,BPNN, SVR	MAPE, RMSE, MAE
[30]	VSA-MLP and BSA-MLP	heating	residential buildings	-	Simulated data	2020	-	-	BP-MLP	RMSE, MAE, R^2
[31]	MLP,SVR	Cooling heating	Residential building	-	Simulated data	2020	-	-	Actual load	R,MSE, RMSE, MAE
[32]	ANN	heating	Residential Buildings	short-term	historical	2020	MATLAB	Sensitivity analysis	traditional calculation method	MSE, R
[33]	EHO-MLP	cooling	Residential Buildings	short-term	simulated	2020	MATLAB	-	HHO-MLP ACO-MLP	RMSE, MAE, R^2
[34]	walking slide method based on ANN	cooling	Factory building	short-term	Historical weather	2020	Python	PCA	WNN, SARIMAX , ElmanRNN , RF, LSTM-RNN, SVR	NRMSE, e
[35]	FFNN	heating	Complex building	short-term	Historical weather	2020	Python	sensitivity analysis	LS L , SVM, Huber Regressor , DT,,RF , Orthogonal Matching	R^2

paper	technique	Type of prediction	Type of building	prediction term	dataset	year	Simulation or real	Feature sele. Tech	comparison of forecasting results	Evaluation metrics
									Pursuit , SGD Regressor	
[38]	DNN	Cooling heating	residential buildings	-	historical	2020	MATLAB+R programming	-	GBM, GPR MPMR	RAAE, MSE, RSR RMAE, R^2, MAPE NS WMAPE,.
[39]	TCN	Heating load	District	short-term	Historical data	2020	-	Standard deviation	RFR, ETR, GBR, SVR, NuSVR, SGD, MLP, RNN, LSTM,	MAE, MAPE, RMSE
[40]	LSTM RNN	Heating	Province	short-term	Historical+ Weather	2020	PyTorch	-	linear, RF, GB	MAPE
[41]	DNN.	Heating	apartment building	short-term	Weather	2016	- simulated EnergyPlus	-	5 DNN with diverse Inputs	R^2 ,MAPE , RMSE
[42]	Deep Learning	Cooling	Commercial building	short-term	Historical original cooling load	2018	Matlab	Deep Belief Network	BPNN, SVM	MAE, R^2 RMSE, MAPE CV-RMSE
[43]	Deep Learning	Cooling	Office building	short-term	Historical	2017	R tool	Deep auto-encoder	-	RMSE, MAE CV-RMSE
[44]	Deep RNN	heating	commercial building	medium-term	Historical weather	2018	python	-	3-layer MLP model	error
[45]	Deep Deterministic Policy Gradient (DDPG)	HVAC	office building	Short-term	Historical weather	2019		Auto encoder	BPNN, SVM, BSAS-BPNN, SVM, BSAS-AE-DDPG	MAE, R2 RMSE
[46]	Multi-Step Ahead Forecasting Method	Heating	District	Short-term	Historical	2019	-	Partial autocorrelation function	Direct XGBoost, Direct DNN,Direct SVR, Actual	MAE, MAPE, CV-RMSE
[47]	LSTM NN	HVAC	building	Short-term	Historical weather	2020	Pytorch	-	Actual load	NRMSE, MSE
[48]	dynamic recurrent NARX	heating	-	Short-term	Measured	2018	matlab		SVR, GPR, BT and Boosted trees	MSE,RMSE PCC
[49]	ensemble learning and stacked auto-encoder (SAE)	cooling	commercial building	short-term	Historical weather	2020			BPNN, SVM, and WT+SVM	MAPE, RMSE, MAE, R2
[52]	SVM	Cooling	building	short-term	Historical	2009	Real	-	ARIMA	-

paper	technique	Type of prediction	Type of building	prediction term	dataset	year	Simulation or real	Feature sele. Tech	comparison of forecasting results	Evaluation metrics
[53]	GA-SVR and GA-WD-SVR	Cooling	Office buildings	short-term ultra-short-term	Historical+ Weather data	2017	MATLAB R2014	-	Self comparison	RMSE MRE R^2
[54]	LS-SVR	cooling	building	short-term	Historical +weather	2010	Simulink+ python	-	Actual, BPNN GML,ARIMA	MAPE
[51]	SVM with Firefly searching	Heating	District	short-term	Historical	2016	-	Grid search	GP ,ANNs , SVM with grid search	RMSE, $R^{2,}$ r.
[55]	SVM-WAVELET	Heating	District	short-term	Historical	2015	-	-	GP + ANN	RMSE, r,R^2
[56]	Wavelet-PLS-SVM	Cooling Heating	Office Buildings	short-term	Historical + Weather	2018	Matlab+SIMCA-P	Sensitivit+ correlation analysis	Wavelet transform, SVM and PLS	MARE, MAE, RMSE
[57]	SVM+ BPNN	cooling	office building	Short-term	Historical weather	2010	-	-	themself	RMSE, MRE
[58]	MSA-SVMR	Cooling	hotel	Short-term	historical	2019	matlab		SA-SVR,VFSA-SVR	EEp, MAE
[7]	Bayesian Network model	Cooling	University Campus	week	Historical+ Weather data	2018	Real	Manually	SVM, ANN	R^2 RMSD
[60]	MNR	Cooling	Public Buildings	short-term	Historical + Weather	2019	MATLAB	sensitivity analysis	MLR, AR, and ARX	MAE,RMSE,EEP,CV, R^2
[61]	Improved MNR	Cooling	Office Building	Daily	Historical Weather	2015	SPSS	distance-correlation	4 prediction models	ARE
[62]	Improved ARX	Cooling	Office building	short-term	Historical Weather data	2019	-	sensitivity analysis	MLR, AR, ARX,	R^2, RMSE, EEP, CV, MAE
[63]	MNR	Cooling	Office building	short-term	weather data. Measured load data	2019	matlab	Sensitivity analysis	MLR, AR, ARX, BP	R^2, RMSE, EEP, CV, MAE
[64]	ARX	Heating Cooling	Office Buildings	Hourly	Weather Measured Cooling	2017	-	-	actual cooling loads	SD, EEP, CV, MAE
[65]	Improved ARX	Cooling	Office Buildings	Hourly	Historical Weather	2018	distance-correlation	-	Actual cooling load+ SVR	PICP
[66]	Time-indexed ARX	Cooling	academic institution	short-term	Historical weather	2014	matlab	-	ANN and ARX	SEE, EEP, CV,

paper	technique	Type of prediction	Type of building	prediction term	dataset	year	Simulation or real	Feature sele. Tech	comparison of forecasting results	Evaluation metrics
										MBE
[67]	Nonlinear Model Predictive Control (NMPC)	Cooling heating	office building	Short-term	Historical weather	2014	MATLAB/Simulink		Actual load	RMSE. MAPE
[68]	Chaos-SVR, SVR WD-SVR, and BP	Cooling	Commercial Building	Short-term	Historical weather	2017				EEP, R2, MBE
[69]	WNN, ELM, SVM, and GA-BP	Heating	Residential Building	Medium-term	indoor temperature and historical	2018				
[70]	MLR, GPR , LMB-NN	Cooling	Office Building	short and medium-term	actual forecasting, climate	2019				R, MAE, MAPE, CV
[71]	TB, boosted tree GPregression, NN MLR, bagged tree,	heating cooling	office buildings	short-term	historical data	2018	MATLAB		Actual + (BRNNs)	RMSE, R MSE, MAE ,CV, MAPE
[72]	SVM, regression tree, FFNN, MLR	heating	district	Short-term	Historical weather	2016	Matlab			NRMSE RMSE
[73]	ARS, ELM , hybrid MARS and ELM	heating cooling	residential buildings	-	Energy Efficiency	2018				WMAPE, MAPE, Cc, RMSE, R^2
[74]	ANN, TF, Process, SS and ARX	HVAC	residential building	-	-	2015	Matlab			AE, APE, Std_{AE} MAX_{AE}, MBE MAE,MSE, RMSE, MAPE, Std_{APE}.RMSE,CV, CC , G, R^2
[50]	NARX RNN,SVM-R RBF , SVM-R polynomial	Cooling heating	Commercial Building	Short-term	Historical weather	2018	-	-	Actual load	MAE and MSE

paper	technique	Type of prediction	Type of building	prediction term	dataset	year	Simulation or real	Feature sele. Tech	comparison of forecasting results	Evaluation metrics
[75]	ABC-ANN, PSO-ANN, ICA-ANN, and GA-ANN	heating	Buildings	Short-term	Historical	2019				R^2, RMSE, MAE
[76]	36 machine learning algorithm	HVAC	Short-term	Smart building	Historical weather	2020	R language			R, RMSE

Le, et al. [75] studied four techniques based on ANN that used to predict the heating load of building. Artificial Bee Colony optimization, PSO, Imperialist Competitive Algorithm, and GA the models hybridized with the ANN to develop ABC-ANN, PSO-ANN, ICA-ANN, and GA-ANN models. The studies show that the utilization of the meta-heuristic algorithms optimized the ANN model very well. The results demonstrate that the GA-ANN outperforms the other three models with highest heating load prediction accuracy.A comparison of 36 machine learning algorithms, which belong to 20 families conducted by Alawadi, et al. [76] to estimate the indoor temperature. A real data used in the comparison while the algorithms is evaluated based on the performance, accuracy, and robustness to weather changes. The comparison result shows that the Extra Tress regressor achieved the highest accuracy and performance over all horizons in terms of R-coefficient and RMSE. Moreover, the findings prove that the accuracy of the best models is not affected when the prediction time increased.

5. Comparative analysis

Through extensive review and summary of the reviewed studies as explained in the Table 1 it is noticed that the majority of the studies use a single zone of building which affect the performance if the model applied to multi-zone area. The most of the studies implement the prediction models for the office building, while the rest is used to implement the model for residential, commercial, institutional, and public buildings. However, the models developed for one type may not appropriate for the other building types because each type of buildings have a diverse attributes. Most of the studies use the weather data or/and historical data while these studies does not take into account the occupancy behavior and indoor humidity as input parameters for the prediction models. However, ignoring these parameters affect the performance of the model by obtain incorrect future prediction load. Additionally, the selected parameters as input to the model affect the model accuracy while the number of parameters has no significant effect on the model accuracy. Most of the prediction models developed off line -that used the prediction history as an input- while a very limited number of models implemented in the cooling and heating systems and used the actual load to predict the future load. A large number of proposed models use the forecasting weather data to develop the model, but most of them did not consider the weather change. The change of the weather produce inaccurate load and produce a problem in the demand power required by building systems. Furthermore, the prediction period considered in these studies is short-term period -hours- except 2 studies considered the medium and long terms prediction. The long term is providing and estimating power demand from 1 month to a year and consequently the power provider can estimate the future demand. On the other hand, the most models used the ANN techniques or merge other technique with ANN to enhance the accuracy and handle the shortcoming in the ANN. Moreover, deep learning techniques are used to improve the models' performance while ensemble techniques that combine several models are used also. However, SVM or SVR obtain the better accuracy when they are compared with other techniques such as ANN, DL, and Regression analysis techniques. The performance of the models is measured using RMSE, MAE, MAPE, and R^2 as the major evaluation methods while a few numbers of studies used other methods such as SEE, EEP.

5.1 Conclusion

To obtain an efficient energy consumption of buildings, developing a suitable cooling and heating load prediction model is required. The utilizing of the data-driven techniques and algorithm to model the cooling and heating system is a significant factor that affects the performance and accuracy of the system. Therefore, reviewing and analyzing the models and techniques which is used to implement the cooling and heating prediction models is significant process to select appropriate forecasting model. The study reviewed the paper published from 2010 to the present time and related to cooling and heating load prediction. This study discussed the different models types by highlighting on the main advantages and explains the disadvantages. These studies classified into artificial neural networks, Deep learning, Support vector machine and Regression analysis models in addition to the studies perform a comparison between several prediction models. As a result a comparative analysis of these techniques is conducted in order to highlight both the advantages and the shortcomings of the prediction studies. Consequently, a number of issues come out from analysis that is the further studies from the researchers such as the input parameters and occupancy behavior.

Nomenclature

Absolute Error	AE
Absolute Percentage/Relative Error	APE
Absolute Relative Error	ARE
Coefficient Of Determination	R^2
Coefficient of Variation	CV
Coefficient Of Variation Of The RMSE	CV-RMSE
Correlation Coefficient	CC
Expected Error Percentage	EEP
Goodness Of Fit	G
Maximum Absolute Error	$MAX_{AE,}$
Maximum Error	MAX
Mean Absolute Error	MAE
Mean Absolute Percentage Error	MAPE
Mean Bias Error	MBE
Mean Relative Error	MRE
Mean Squared Error	MSE
Mean Squared Normalized Error Performance	MSNEP
Nash–Sutcliffe Coefficient	NS
Normalized Root Mean Square Error	NRMSE
Pearson Coefficient	R
Prediction Interval Coverage Probability	PICP
Relative Average Absolute Error	RAAE
Root Mean Square Error	RMSE
Root Mean Squared Deviation	RMSD
Root Means Absolute Error	RMAE
Standard Deviation	SD
Standard Deviation Of Absolute Error	Std_{AE}
Standard Deviation Of Absolute Percentage Error	Std_{APE}
Standard Error Of Estimate	SEE
Weighted Mean Absolute Percent Error	WMAPE

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