Chapter 2

Literature Review

This chapter focuses on the background and recent works that lead to the work of this thesis. It discusses some key literature with its advantages and shortcomings. Furthermore, this chapter also explains a research gap in energy forecasting in smart buildings. Existing related works on energy forecasting in smart buildings can be categorized into the following subcategories (Figure 2.1).

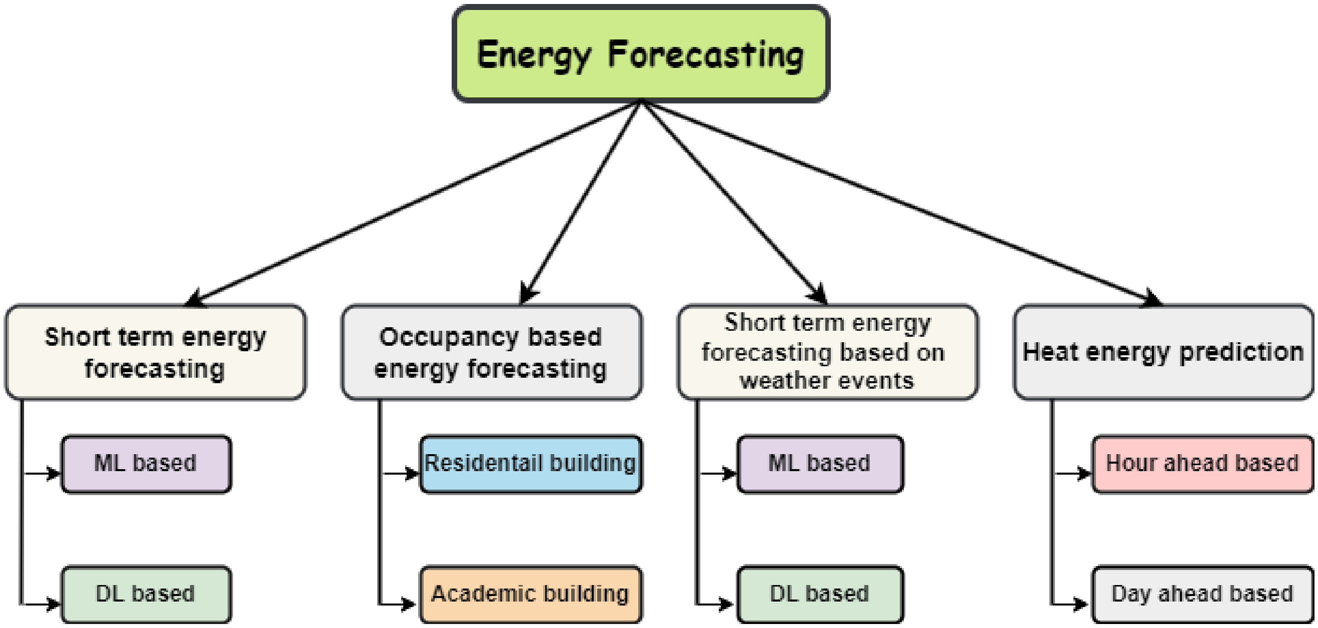

Figure 2.1: Categories of existing related works

2.1 Short-term energy forecasting

This section reviews the literature work on short-term energy forecasting in smart buildings. Khalil et al. [20] implemented federated LSTM for short-term load forecasting. In this paper, both univariate and multivariate models of LSTM were built. However, they did not compare the results by tuning various hyperparameters, such as the number of layers, lag, and number of neurons. Tavakoli et al., [21] implemented a Bi-LSTM model for energy forecasting and tuned various hyperparameters, such as lag, number of layers, and number of neurons, to obtain the optimal results for both univariate and multivariate data and claimed that BiLSTM performs better compared to conventional LSTM. Mendes et al.,[22] implemented GRU and LSTM models for univariate and multivariate data to observe and compare the results obtained by tuning various hyperparameters such as lag, number of layers, and number of neurons. GRU was the better predictor in the studies with univariate data than LSTM.

The work done by Lee et al. in [23] was focused on low-cost energy forecasting systems for small and middle-sized office buildings. Zhang et al.,[24], used a weighted hybrid support vector regression model to forecast the energy consumption of institutional buildings on a half-hourly and daily basis. This work gives low MAPE for daily and half-hourly datasets compared to state-of-the-art methods like Genetic algorithm (GA) and Particle swarm optimization (PSO). Amber et al.,[25] used multiple regression to predict the daily energy consumption of a building. They did not address the model with new weights, and no accurate information was available for building occupancy. Nikiforov et al.,[26] proposed load prediction for large commercial buildings using RNNs.

The work done by Chen et al., [27] stated that Support Vector Regression (SVR) is used to forecast office buildings' electrical load and find demand response energy for office buildings. The limitation of this work is that they did not consider residential buildings in all situations and considered only office buildings. Jihad et al.,[28] pro-

Table 2.1: Summary of work related to short energy forecasting in smart buildings

Sl No	Reference and Year	Models Used	Short-Term or Long-Term	Accuracy Low or High	Limitation
1	Khalil et al. 2021 [18]	LSTM	Short-term	Low (90%)	Not compare the results by tuning various hyperparameters such as number of layers, lag, and number of neurons.
2	Tavakoli et al., 2019 [19]	Bi-LSTM	Short-term	Low (87%)	Not performed well on large volume of data. It is limited to small set of data points
3	Mendes et al., 2021 [20]	GRU and LSTM	Short-term	Low (92%)	Considering the single features from the dataset.
4	Blazquez Garcia 2021[21]	Seasonal linear Quadratic and Multiple regression	short-term	Low(92%)	Loses its ability to generalize to new or unseen data .
5	Zhang et al., 2016 [22]	SVR GA PSO	short-term	Low (86%)	Low MAPE for daily and half-hourly datasets compared GA and PSO optimization .
6	Amber et al., 2017 [23]	Regression Models	short-term	Low(87%)	Not address the model with new weights, and no accurate information for building occupancy.
7	Nikiforov et al 2019 [24]	RNN	short-term	High(96%)	Not considered all features in the dataset.
8	Chen et al., 2017 [25]	SVR	short-term	Low (90%)	Did not consider residential buildings in all situations & considered only office buildings.
9	Li et al., 2020 [28]	Regression Models	Long-term	Low (92%)	Physical parameters of building's not yet considered for thermal and daily electricity forecasting.
10	Jihad et al., 2018 [26]	ANN	Short-term	High (98%)	Considering only an individual climate zone for the energy prediction of the building.
11	Kim et al. 2019 [27]	ANN	Short-term	Low (85%)	Different models & different data for institutional buildings are not used.
12	Iqbal et al., 2021 [29]	ANN	Short-term	High (95%)	Fails to give a good value of R^2, High error metrics in terms of MAE & RMSE are observed.

posed an artificial neural network (ANN)-based approach to predict energy loads for residential buildings. The limitation of this method is that it considers an individual climate zone for the energy prediction of the building. Kim et al.,[29] proposed an ANN method to forecast the peak energy demand for non-residential buildings. The limitation of this paper is that it uses the same model for different data for other institutional buildings. Li et al.,[30] used a hybrid model to forecast energy for buildings using a fuzzy system and wavelet transforms. Iqbal et al.,[31] proposed forecasting the energy consumption of smart buildings using ANN and the Internet of Things (IoT). The paper fails to provide a good value of R^2, and high error metrics in terms of MAE and RMSE are observed. A brief comparison of existing short-term energy forecasting is shown in Table.2.1

2.2 Occupancy-based energy prediction

This section provides a detailed review of building energy prediction based on occupancy. R. Sevlian et al. found that forecasting energy for a limited number of customers is very challenging [32]. This work lacks scalability and generalization for larger datasets and different building structures. F. L. Quilumba et al. proposed a k-means-based energy prediction algorithm that achieved 11% gain in energy prediction accuracy [33]. However, k-means clustering is unsuitable for capturing more intricate patterns, such as temporal dynamics or interactions between different features. Y. Wang et al. proposed an ensemble of forecasts using hierarchical clustering and deep learning models. It improves building energy prediction performance [34]. This approach suffers from its high complexity. Therefore, it requires high computational resources.

The work done by R. Tibshirani et al., proposed a lasso regression-based energy prediction model[35] where lasso regression handles feature selection. However, it does not capture long-term energy consumption time series dependencies. Lu et al., [36] proposed an LSTM model for short-term load forecasting of building energy consump-

Table 2.2: Summary of work related to occupancy-based energy forecasting in smart buildings

Sl No	Reference and Year	Models Used	Short-Term or Long-Term	Accuracy Low or High	Limitation
1	F. L. Quilumba et al. [31]	k-means	Short-term	High(95%)	Not able to capture more intricate patterns
2	Lu et al. 2018 [34]	LSTM	Short-term	Low(86%)	Did not consider occupancy count & external weather conditions such as temperature and wind.
3	Ahmed et al. 2020 [99]	Deep learning algorithms	Medium & Long-term	Low(86%)	Does not investigate the interpretability of the deep learning models.
4	Kim et al. 2017 [43]	Linear Regression	Short-term	Low(78%)	Limitation of this method is low in terms of accuracy.
5	Mahdavi et al. 2016 [44]	Weibull distribution	Medium & short term	High(96%)	occupancy are not considered
6	Kim et al. 2020 [51]	BR QNBP SCG LMBP	Short-term	Low(91%)	Recorded high error rates like 1.07- 2.23
7	Wang et al., 2023 [38]	LR ANN LSTM GBRT	Short-term	High (95%)	Not able to examine how regularly updating sample weights are influenced by validation sets.
8	Wei et al. 2019 [54]	ELM FFNN Ensemble	Short-term	High (93%)	Computational time complexity is high.
9	Anand et al. 2021 [47]	SVR RF ANN-DNN ANN-FF, GB	Long-term	Low (79%- 85%)	Mean Absolute Error (MAE) is very high.
10	Ouf et al. 2017 [30]	Statistical and Machine Learning	Short-term	Low (79%)	The R2 is 0.53(CO_2) based occupancy, 0.70 in the case of WiFi-based occupancy, both is 0.79. The R2 is low compared to existing techniques.
11	Fatehi et al., 2023 [60]	GRU LSTM	Short-term	Low (79%)	Investigated and explored GRU-based prediction models to optimize energy is required for occupants' activities in SB.
12	Tsalikidi et al., 2024 [58]	ML ANN	Short-term	High (95%)	Getting more actual data from the real world helps them to make better guesses and be more dependable.

tion. This paper uses LSTM networks to capture the temporal dependencies. The major drawback of this approach is that it does not consider additional features like occupancy count and external weather conditions. Alzahrani et al., [37] provided a comprehensive review for building energy consumption forecasting using machine learning techniques. This work focused on simple features and did not consider complex features such as weekdays and hours in a day in the form of lag in hours during the prediction. It affects the accuracy of the energy prediction and lacks detailed empirical analysis or performance comparisons between different models.

Ghosh et al., [38] proposed an ensemble method for energy consumption prediction in smart buildings. The major drawback of this approach is that it suffers from huge computational complexity and scalability problems. N. G. Paterakis et al.,[39] compared deep learning and traditional machine learning methods for aggregated energy demand prediction. However, this study did not extensively address the interpretability of the deep learning models, which limits their practical applicability in scenarios where interpretability is crucial. Z. Wang et al.,[40] introduced a novel ensemble learning approach for building energy use prediction, which improves model prediction accuracy. The demerit of the paper is there is a limited discussion on the practicality of the model implementation in real-time.

The research work on energy prediction done by P. Vijayan et al., [41] utilized machine learning and artificial intelligence for energy efficiency, contributing to energy consumption prediction in low-energy buildings. However, the paper lacks detailed insights into the generalizability of the proposed models across diverse building types and geographical regions. Predictive modeling for energy consumption using ANN was explored [42]. T. Ahmad et al., developed supervised machine learning models for predicting short-, medium-, and long-term energy in distinct building environments [43]. The limitation of this approach is the absence of a comparative analysis of the models' performance across diverse building types and usage patterns. The other limitation is that the model needs to be retrained when the new data is considered. There is limited discussion on the practicality of the model implementation in real-time.

This paper discusses closely related work in plug load prediction based on occupancy. The plug load is the total energy consumed by using various electronic equipment such as printers, fans, chargers, etc. [44]. The statistical and regression models are vital in predicting plug load based on building occupancy. Kim et al., [45] used linear regression to forecast plug load with occupant count in office and campus buildings in Philadelphia. 0.68%-0.78% of correlation coefficients achieved between plug loads and occupant count. The imitation of this method is low in terms of accuracy. Mahdavi et al., [46] developed Weibull distribution to predict plug load with occupant count. His method performs better than linear regression in peak load prediction based on building occupancy. Many studies have addressed occupant behavior issues with different types of buildings by focusing on different influential factors and measurements. Halidi et al., [47] explain the occupancy pattern analysis and how it influences other environmental factors such as indoor and outdoor temperature. Yun et al. [48] show the relations between occupancy patterns, temperature, and CO_2. Anand et al. [49] demonstrated how occupancy diversity and weather conditions correlate in predicting total energy consumption and greenhouse gas emissions in buildings.

The work done by Amjady et al., [50] used ARIMA for daily peak load prediction and hourly load electricity prediction in Iran in buildings. Epison et al., [51] achieved 90% of R^2 squared accuracy in predicting electricity in a building using ARIMA. Kouhi et al., [52] proposed a neural network-based approach to predict electricity consumption in New York. Kim et al., [53] developed the four Back-Propagation Neural Network (BPNN) algorithms such as Bayesian Regularization (BR), Quasi-Newton Back-Propagation (QNBP), Scaled Conjugate Gradient (SCG), and Levenberg-Marquardt Back-Propagation (LMBP) to explore how plug load data, occupancy level, and weather factors influence in the electricity consumption of buildings and predict the electricity usage of buildings in seasonal changes. The limitation of this method is that it shows high error rates like 1.07–2.23%. Khanna et al., [54] explained how living standards affect a building's energy consumption and account for 55% of total energy consumption, which is increased yearly by an average of 1.1%.

Research work of Ding et al., [55] used the Markov model and the Probability function to predict energy consumption and count occupancy based on the Passive Infrared Sensor (PIR) sensor. The limitation of this paper is that it did not consider other environmental factors such as temperature, weather, etc. Wei et al.,[56] predicted the energy consumption of buildings and estimate the occupancy in buildings based on the CO_2 sensor using an ensemble, Elaboration Likelihood Model (ELM), and Feed-Forward Neural Network (FFNN). This method's limitation is that 0.92% and 0.93% are recorded energy predictions with occupancy considered and energy predictions with occupancy not considered, respectively.

Markovic et al., [57] developed LSTM to predict the energy consumption for the day ahead, considering the occupancy data for a building in Abu Dhabi, United Arab Emirates (UAE). Anand et al., [58] forecasted the energy consumption using Support Vector Regression (SVR), Random Forest (RF), Deep Network-based Artificial Neural Network (ANN-DN), Artificial Neural Network Feed Forward (ANN-FF) and Gradient Boosting (GB) by considering the occupancy data for institutional buildings. The limitation of this method is that the recorded mean absolute error is very high. Zuraimi et al., [59] developed the ANN and SVM to estimate occupancy count based on the CO_2 sensor to improve buildings' Indoor Environmental Quality (IEQ). Energy consumption and IEQ are directly linked to the occupancy count of buildings. The authors detail how the energy efficiency of a building is improved by counting the occupancy of a building.

The work on occupancy-based energy consumption done by Irankhah et al., [60] use BiLSTM, ConvLSTM, and many machine learning models to create a machine learning system for accurately forecasting short-term energy for residential buildings. The author Mahjoub et al., [61] used the smart home occupancy prediction technique based on environmental variables such as CO_2, noise, and relative temperature by machine learning method and forecasting strategy. An LSTM was used, and the proposed method was improved by using a Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Faiq et al.,[62] used LSTM to predict energy consumption in a building, using weather forecasts from the Malaysian meteorological department. The model outperformed SVR and Gaussian Process Regression (GPR) when tested with data from the multimedia university, malacca Campus. The demerits of this work are that to make accurate predictions, LSTM needs a lot of past data, and it also benefits from using other factors like temperature and schedules. There is a lack of focus on making the model even more accurate by adding features like how many people are in the building.

All the above methods mentioned are used to find plug load prediction based on different features such as light, plug, and HVAC with occupancy in various types of buildings. Most current work uses statistical methods, and few use machine learning approaches. According to the studies, no deep learning approach is used to predict plug load in a building by considering both occupancy and other environmental factors. Therefore, it focuses on deep learning and machine learning approaches to predicting plug load based on the occupancy of building rooms. A brief comparison of existing occupancy-based short-term energy forecasting methods is shown in Table 2.2

2.3 Energy prediction based on extreme weather events

The literature review on short-term energy prediction with extreme weather events is explained in this section. Yu et al., [63] explores short-term wind power forecasting based on extreme weather. This paper consists of a power time series trend discrimination method and an Inflection Point (IP) detection method to accurately identify Extreme Weather Periods (EWPs). Feature recognition is carried out for power time

Table 2.3: Summary of work related to weather based on short-term energy prediction

Sl No	Reference and Year	Models Used	Short-Term or Long-Term	Accuracy Low or High	Limitation
1	Tu et al. 2023 [61]	ARIMA LSTM GRU	Short-term	Low(87%)	Dost not consider the impact of extreme weather on wind power on a multi level scale.
2	Moazami et al. 2019[62]	Statistical model	Long-term	Low(86%)	Not considering the effects of urban/microclimate, as the effects of climate change might be amplified or diminished at the urban scale
3	Sarmas et al., 2023 [63]	StackLSTM BiLSTM CNN-LSTM ConvLSTM	Short-term	Low(90%)	Feature selection of data and preprocessing techniques are not done.
4	Watson et al. 2022 [64]	Regression methods	Short-term	Low(88%)	Limitation of this method is time complexity of the model high.
5	Yang et al 2023 [65]	BiLSTM GRU LSTM BP ELM	Short-term	High(96%)	The accuracy of the model less for large volume of data.
6	Kosovic et al 2020 [66]	Ensemble Statistical	Short-term	Low(91%)	High error metrics are recorded.
7	Guo et al 2020[67]	MINLP	Short-term	High(93%)	Training time and simulation time considerably high.
8	Tervo et al 2019 [68]	MLP	Short-term	Low (88%)	Data imbalance is high and for missing data they are using old basic techniques.
9	An et al 2020[69]	Adaboost PSO-ELM	Short-term	High (98%)	Training sample of the data are not selected based reconstruction.
10	Wang et al 2021 [70]	LSTM	Short-term	Low (83%)	Forecasting accuracy for various client categories are low.

series with multiple weather models. Wind power probabilistic forecasting is developed using GRU and an improved kernel density estimation method. The limitation of this method is that it does not consider the impact of extreme weather on wind power on a multi-level scale. Moazami et al., [64] explained the impacts of long-term patterns of climate change and extreme weather conditions on the energy performance of buildings. The limitation of this method is not considering the effects of urban/microclimate, as the effects of climate change might be amplified or diminished at the urban scale.

The work done by Sarmas et al., [65] suggest a meta-learning technique to enhance PV system deterministic forecasts one hour in advance by dynamically combining the basis forecasts of several DL models to discover the optimal conditions for each model. The limitation of this method is feature selection and data preprocessing techniques are not performed. Watson et al., [66] describes a model for accurately predicting power outages in extreme weather events. The limitation of this method is high time complexity. Yang et al.,[67] proposes a wind power ultra-short-term prediction method based on NWP wind speed correction and double clustering division of transitional weather process. The limitation of this method is the accuracy of the model less for large volumes of data.

Kosovic et al.,[68] explained wind power forecasting systems integrating artificial intelligence and numerical weather Prediction. The limitation of this method is high error metrics. Guo et al., [69] developed a fragile model to evaluate the nodal SCF probability considering the insulation aging of equipment and extreme weather conditions. The limitation of this method is that it suffers from Short Circuit Faults(SCFs). Tervo et al., [70] described a machine-learning method to predict the damage caused by storms. The entire forecast technique involves tracking a track of storm cells, categorizing them according to their ability to cause harm to power grid operators, and recognizing storm cells from Constant Altitude Plan Position Indicator (CAPPI) weather radar images by contouring them with a solid 35-dBZ threshold. The limitation of this method is that data imbalance is high, and for missing data, they are using the old basic approach.

The work done by An et al., [71] proposed a short-term wind power prediction based on a particle swarm optimization-extreme learning machine model combined with the adaboost algorithm. The limitation of this method is that training samples of the data are not selected based on reconstruction. Wang et al., [72] explained the short-term residential load forecasting model based on LSTM recurrent neural network that considers weather features. The limitation of this method is the difficulty in interpreting the forecast analysis and the complexity of the selection of model parameters. The comparison of existing short-term energy prediction based on extreme weather events is shown in Table 2.3

2.4 Heat energy prediction

Recent work on heat energy prediction for smart buildings with occupancy has been explained in this section. Ding et al.,[73] explain the short-term heating load and predict the heating load 24 h ahead and 1 h ahead, respectively. The limitation of this work is that it misses lag in different hours. Van et al., [74] illustrated that occupants and buildings are equally important for energy and heat demand prediction. The limitation of this approach is that it does not consider features such as temperature, CO_2, and etc. Heydarian et al.,[75] described many ways to understand the energy required for a building, such as variations in electrical appliances used and occupant behaviors. The limitation of this approach is that it does not compare more varied geographic places to foster a greater comprehension of the cultural parallels and discrepancies in the relationships between heat demand and occupants. Yang et al.,[76] stated that heating consumption depends on household characteristics such as occupants' living style, ages, etc. The limitation of this work is that it requires a better processing time. Alberini et al., [77], explained how occupants utilize the resources and what electrical components are used in the household. On the other hand, Anderson et al., [78], have

Table 2.4: Summary of work related to heat energy prediction in smart buildings

Sl No	Reference and Year	Models Used	Short-Term or Long-Term	Accuracy Low or High	Limitation
1	Ding et al. 2019 [71]	Markov model Probability function	Short-term	Low(88%)	Did not consider other environmental factors such as temperature, weather.
2	Huo et al., 2024 [93]	CEEMDAN SE-EC BiLSTM	Long-term	High (97%)	Discovering the optimal settings to enhance the predictions is not done.
3	Hua et al. 2024 [94]	MLR ANN	Short-term	Low (93%)	It is hard to figure out the hyperparameter. calculating a building's heat energy, it doesn't consider occupancy and indoor temperature.
4	Alaraj et al., 2023 [95]	ML FFNN	Long-term	Low(89%)	Not performed DSM applications, like making operational decisions, responding to demand among other purposes.
5	Ding et al 2018 [75]	SVR MLP	Short-term	Low (87%)	24 hour and 1 day ahead prediction is performed but missing lag in hours.
6	Mahjoub et al., 2023 [90]	GA PSO LSTM	Long-term	Low(91%)	Low error metics recorded.
7	Trotta et al 2020 [77]	k-Means	Short-term	Low(87%)	Not considered all features in the dataset.
8	Le et al 2019 [88]	ABC-ANN PSO-ANN ICA-ANN GA - ANN	Short-term	High (93%)	Computational processing power is high.
9	Lumbreras et al 2022 [96]	Multivariable regression Multistep model	Long-term	Low (83%)	Only inputs into the model are calendar data and meteorological variables.
10	Fouladfar et al 2023 [97]	ANN	Short-term	High (95%)	Training time and simulation time considerably high.

mentioned heating practices in people's everyday life, like what they use for their daily needs (showering, laundry routine, etc.). The demerits of this method are it does not consider other features such as CO_2 and temperature. Trotta et al., [79], explained the daily usage energy patterns with occupants using smart meter data. The limitation of this method is that it does not consider all features in the dataset. Leiria et al., [80], explained that hourly heating consumption had been analyzed recently using a smart meter. Gianniou et al., [81], understand the correlations between household characteristics such as the number of persons present in the house in terms of adults, aged people, and kids. In both cases missing lag in different hours.

According to Hansen et al.,[82], it is essential to investigate energy demand patterns by exploiting high-resolution data and to get further knowledge on peak heat demand patterns. It is required to get detailed information on households to characterize. Furthermore, Linear Regression (LR) in the 1980s [83] and Auto-Regressive Integrated Moving Average (ARIMA) in 1984 [84] are used to predict building heat load prediction. Recently, Support Vector Machine (SVM) [85], ANN [56], Regression Tree (RT) [86], and RF [87] to predict the heat load of buildings from the limited number of features. The heat energy consumption prediction for 168 h is done in Finland by Fang et al., [88] using a combination of weather, social factors, and time series data by an auto-regressive model.

The research work done by Jovanovic et al., [89] used an ANN model to forecast daily heat demand for different university rooms. It proved that as compared to a single method, the ensemble method performs better for prediction. Le et al.,[90] used four different combinations of ANN such as Artificial Bee Colony optimization (ABC-ANN), PSO-ANN, Imperialist Competitive Algorithm (ICA-ANN), and GA with ANN to predict heat load in a building. Out of these models, GA-ANN outperforms the other models with better accuracy. The limitation of this method is that hyperparameter tuning is not performed properly. Roy et al., [91] used machine-learning models such as

Multivariate Adaptive Regression Splines (MARS), ELM, and a combination of MARS and ELM models to forecast heat load prediction based on a specific parameter in a building. The MARS performs better than other models for heat load prediction, but the processing power is higher, and the computation time increases. Furthermore, the hybrid model performs better than MARS in terms of RMSE.

The work done by Massana et al., [92] used MLP to forecast heat load for non-residential buildings and the demerits it fails to capture sequential information. Buddhahai et al., [93] used K-means clustering and decision tree methods to predict energy for home appliances. The demerits of this paper are not appropriate for dynamic environments. The demerit of this paper is it is not appropriate for a dynamic environment. These demerits can be overcome by applying RNN and LSTM. The specialty of RNN is that it is designed for time series data analytics, and it captures essential data features. The LSTM is designed to handle long sequential data. Therefore, the LSTM is intended to predict heat load for smart buildings. Wang et al.,[94] explained that short-term heating load prediction models predict the heating load 24 h ahead and 1 h ahead, respectively. Huo et al., [95] describe a new way to predict energy use more accurately, essential for planning the electricity grid and more effective use of renewable energy sources. It breaks down the energy use data into smaller parts called IMFs using a CEEMDAN method. Then, it checks how complex these parts are using Sample Entropy (SE) and simplifies them further. After that, it predicts these parts using a special kind of artificial intelligence called BiLSTM. The work started by Hua et al., [96] used the Multiple Linear Regression (MLR) and ANN to predict the heat prediction of buildings. It is essential to plan how much district heating is needed in Finland. The Work done by Alaraj et al., [97] used machine learning to predict and optimize electricity use for heating and cooling in an office building a year ahead. Lumbreras et al., [98] explained the novel data-driven model for characterizing and predicting heating demand in buildings connected to a DH network. The limitation of this method is that the only inputs into the model are calendar data and meteorological variables, and low accuracy is obtained for hourly data resolution. Fouladfar et al., [99] developed an ANN-based model for thermal load and indoor temperature prediction in residential buildings. The limitation of this method is that the training time of the data is considerably high. A brief description of existing heat energy prediction in smart buildings is shown in Table.2.4

2.5 State_of_the_art

The energy forecasting for smart buildings can be classified into two main categories in the thesis. With occupancy and without considering occupancy. Energy forecasting models did not include occupancy data in real time; instead, they relied on previous energy usage and environmental data. These models concentrate on outside variables such as past consumption trends and meteorological conditions. A popular time series forecasting model that performs well with univariate time series data is ARIMA (AutoRegressive Integrated Moving Average). While seasonal and trend components can be captured by ARIMA, dynamic shifts and non-linear patterns are difficult for it to handle. Seasonal ARIMA, or SARIMA, is an extension of ARIMA that takes seasonality into account. Because of this, it works well to capture patterns of seasonal energy consumption, such as daily or annual cycles. Limitations of these models are haveing trouble in reflecting intricate, non-linear relationships between various factors influencing energy use since they presuppose linearity. Additionally, they don't scale well with multivariate data, such as meteorological or other external variable data. Applications of Support Vector Regression (SVR) include non-linear energy forecasting. SVR works well for small datasets, but it might not work as well with real-time or high-dimensional data. Gradient Boosting Machines (GBMs) and Random Forests: Because these ensemble learning methods can handle non-linear data, they have proven useful in energy forecasting. By using several decision trees to reduce bias and volatility, they increase the accuracy of their forecasts. Limitations of these are careful feature engineering is needed because these models do not directly incorporate temporal dependencies in the data, such as time lags or sequences. An adaptable model for identifying non-linear correlations in energy data is an artificial neural network (ANN). Although ANNs are good at learning from past experience, they can overfit and need big datasets to produce accurate forecasts. Recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) may identify long-term dependencies in time-series data. Because LSTMs can handle sequential data, like past energy usage and meteorological data, they are especially helpful in energy forecasting. Limitations: When abrupt changes in building consumption occur (e.g., an unforeseen event producing high energy demand), these models may introduce inaccuracies since they do not take occupancy patterns into consideration.

Occupancy-driven models may dynamically change forecasts based on the amount of people in the building, leading to more precise and effective energy management. Regression-Based Models: These models use real-time or historical occupancy data (e.g., number of occupants, room utilisation) as an additional component. Although they increase forecast accuracy, their training requires large amounts of labelled occupancy data. With occupancy features, Random Forests and Gradient Boosting Machines are two algorithms that can incorporate occupancy data to improve predictions. For instance, occupancy data can function as a feature in conjunction with energy costs, temperature, and time of day. Limitations: The quality and resolution of occupancy data determine how well these models function, and they still mostly rely on feature engineering. The details of the work has expressed in Table.2.5

2.6 Research Gap

Energy optimization in short-term energy forecasting for smart buildings involves data analysis and efficient prediction methods to manage energy consumption. This process

Table 2.5: State of the art on energy forecasting for smart buildings

Category	Advantages	Disadvantages
Without Occupancy	Easier to implement, can use historical energy and weather data effectively, works for aggregate-level forecasting	Limited adaptability, cannot handle real-time variations due to human activity or unexpected changes
With Occupancy	More accurate and dynamic, accounts for real-time usage variations, improves energy efficiency	Requires real-time sensor data or reliable occupancy forecasts, higher data and computational requirements
Machine Learning with Occupancy	Incorporates a wider range of influencing factors, flexible for real-time or scheduled energy management	May require advanced feature engineering, can be limited by the quality of occupancy data
Deep Learning Methods	Excellent at capturing non-linear, complex relationships in multivariate time-series data	Computationally expensive, may require large datasets and extensive training time

includes forecasting energy demand and adjusting building systems to minimize energy usage while maintaining occupant comfort. Energy usage can be predicted more effectively by analyzing occupancy patterns, occupants' numbers, time of day, day of the week, and historical occupancy trends. Following are the major research gaps that are found in the above state-of-the-art existing research works.

- Due to the volatile nature of single-user power consumption, the accuracy is low in the existing literature despite the state-of-the-art approaches being applied.
- Most models are based on Machine Learning-based algorithms like SVM, RF, XGBoost, etc., and perform energy consumption for a few seconds to a few minutes. Missing hours in different lags.
- Poor Performance from machine learning models in terms of evaluation metrics such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), R Squared (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

- Less work has been performed on considering univariate and multivariate data in short-term energy forecasting.
- There has been less research on short-term energy forecasting for smart buildings based on extreme weather events.
- Deep learning techniques and Hybrid models can be used to increase accuracy.
- Less work has been performed on room-wise energy consumption for smart buildings.