Chapter 2

Literature Review

This chapter presents an overview of ML, DL (DL),ensemble learning, and state-of-the-art. We discuss related work on energy forecasting (EF) in Section 2.1. Some literature on occupancy based in Section 2.2, and occupancy based EF in Section 2.3. Section 2.4 discusses the research gap in the literature review and at last research plan in Section 2.5

This chapter offers a thorough and detailed exploration of the background and recent advancements in research that underpin the foundation of this thesis. It delves into the critical body of literature pertinent to the study, emphasizing both the strengths and weaknesses of existing works. Through a rigorous and analytical examination of prior research, significant gaps in the study of LTE consumption in SBs are identified. These gaps are pivotal in shaping the goals and objectives of this thesis, as they highlight areas where further investigation is needed to advance the field.

Additionally, this chapter organizes and presents related works in a structured and logical manner, aligning them with the overall framework of the thesis. The literature is categorized into distinct subsections, each corresponding to specific themes or topics addressed in the thesis. This approach ensures a clear and comprehensive understanding of previous research efforts, including the methodologies employed and their relevance to the proposed work. By systematically analyzing and categorizing existing studies, this chapter not only underscores the need for continued research but also provides a strong rationale for the contributions of this thesis. It demonstrates how the proposed work aims to address the limitations and challenges identified in prior research, thereby advancing knowledge in the field of LTE consumption in SBs.

2.1 Related Work on EF

In recent years, significant progress has been made in EF for SBs, driven by advancements in ML, IoT, and data analytics. Techniques like time-series analysis, neural networks, and ensemble methods have improved prediction accuracy by incorporating factors such as weather and occupancy. However, challenges like data quality, computational complexity, and long-term energy forecasting (LTEF) remain. Continued innovation is needed to develop more robust and scalable solutions for efficient EM in SBs.

2.1.1 LTEF

Accurate energy consumption forecasting plays a critical role in optimizing building EM. Over the years, several methods have been developed, broadly categorized into statistical, ML, and DL approaches. This review follows a progressive structure: starting with statistical methods, then transitioning into ML as a response to their limitations, and finally to DL, which addresses challenges in both prior approaches.

Statistical models have traditionally served as the foundation for EF. Among them, the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model has been widely used due to its ability to capture trends and seasonality in time series data. Blázquez-García et al. [9] employed SARIMA for EF in non-residential buildings, effectively modeling periodic patterns in energy usage. However, the model's accuracy was limited in more complex environments, especially those influenced by non-linear and dynamic human activities.

Support Vector Regression (SVR) has also been adopted to overcome some linearity limitations. Zhang et al. [10] introduced a weighted hybrid SVR model that outperformed several traditional methods, including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), showing lower Mean Absolute Percentage Error (MAPE). Similarly, Chen et al. [11] utilized SVR for short-term energy forecasting (STEF) in office buildings, though their focus was restricted to non-residential settings, limiting broader applicability. Li et al. [12] compared regression and classification models but omitted key physical building parameters, which could have enhanced model robustness. Amber et al. [13] also explored regression methods, though they suffered from outdated model weights and a lack of real-time occupancy data.

Despite their widespread use, statistical approaches exhibit several limitations. These include an inability to model non-linear relationships in complex environments, poor adaptability to rapidly changing patterns, a heavy dependence on extensive domain knowledge for effective feature engineering, and limited scalability across multiple building types or diverse climate conditions.

To address these shortcomings, researchers have turned to ML techniques, which can learn from data without being explicitly programmed. ML models, particularly Artificial Neural Networks (ANNs), offer the ability to approximate complex and non-linear relationships in energy consumption. Jihad et al. [14] developed an ANN-based model for residential buildings, demonstrating improved forecasting accuracy over statistical methods. However, their reliance on data from a single climate zone restricted model generalization. Kim et al. [15] implemented ANN to forecast peak energy demand in non-residential buildings, but a one-size-fits-all approach across DSs compromised specificity.

Beyond ANNs, Li et al. [12] introduced a hybrid model combining fuzzy logic with wavelet transforms, which aimed to better capture the complexity of energy data. Jose et al. [16] proposed EMANet, a ML-based system that optimized energy efficiency in smart settings. Although effective, its success was contingent on accurate data inputs and compatibility with existing infrastructures. Alotaibi et al. [17] further reduced forecasting errors using ML models, though they required continuous model updates and were sensitive to data quality.

ML addressed several limitations of statistical models by improving the handling of non-linear patterns, offering better generalization from historical data, and reducing reliance on manual feature engineering. However, new limitations emerged, such as degraded performance with noisy or insufficient data, overfitting on small DSs, and the lack of temporal memory and sequential awareness capabilities essential for time-series data like energy consumption.

DL, an advanced subfield of ML, emerged to overcome these limitations by automatically learning hierarchical representations from data, particularly suitable for temporal and spatial EF. Khalil et al. [18] introduced federated LSTM networks for STEF in SBs. While innovative in preserving data privacy, their model lacked a comprehensive hyperparameter optimization strategy. Siami-Namini et al. [19] addressed this by using Bi-LSTM and fine-tuning key parameters, demonstrating superior performance over traditional LSTM models.

To compare model variants, Mateus et al. [20] evaluated LSTM and GRU on univariate and multivariate DSs, with GRU proving more efficient in certain contexts. Despite success, socio-economic and behavioral influences on energy consumption were not considered in these models. Nikiforov et al. [21] used RNNs for large commercial buildings but underutilized the potential of the dataset. Iqbal et al. [22] integrated ANN with IoT technologies, though the model suffered from low R^2 scores and high error margins.

Gunawardhana et al. [23] highlighted the potential of DL in creating power baseline models using CNNs and RNNs, while also acknowledging key challenges like data quality, system integration, and resource intensity. Erten et al. [24] discussed the benefits of models like ANFIS-IC but emphasized similar concerns. Ibude et al. [25] proposed a hybrid CNN-LSTM model capable of detecting both spatial and temporal trends, outperforming simpler architectures. Nevertheless, such models require significant computational resources and are sensitive to data quality and model complexity. Lee et al. [26] contributed to the field by focusing on cost-effective DL models tailored for small and medium buildings.

At last, our hybrid DL models successfully addressed the limitations of ML by capturing sequential dependencies via RNNs, LSTMs, and GRUs, automatically learning features from raw data (reducing manual intervention), and delivering higher forecasting accuracy in dynamic and complex scenarios. However, they also introduced challenges such as high computational costs, a need for large labeled DSs, and difficulties integrating with legacy systems in real-world settings.

2.2 Related Work on predicting energy usage based on occupancy patterns.

2.2.1 Challenges in Energy Prediction: A Review of Modern Approaches

In the early stages of EF research, methods such as box-plot analysis were applied to capture energy consumption trends. Liu et al. [27] employed a box-plot analysis approach for predicting energy consumption and efficiency. While this method offers clear visual insights into energy usage patterns, it lacks the ability to capture

Table 2.1: Summary of work related to STEF in SBs

Sl No	Reference and Year	Models Used	ST or LT	Accuracy Low or High	Limitation
1	Khalil et al. 2021 [1]	LSTM	Implemented federated LSTM for STLF. In this, both univariate and multivariate models of LSTM were built. ST	Low (90%)	Not compare the results by tuning various hyperparameters such as number of layers, lag, and number of neurons.
2	Siami-Namini et al., 2019 [2]	Bi-LSTM	ST	Low (87%)	Perform EF and tuned various hyperparameters, such as lag, number of layers, and the number of neurons, to obtain the optimal results for both univariate and multivariate data Not performed well on large volume of data. It is limited to small set of data points
3	Mendes et al., 2021 [3]	GRU and LSTM	Compare the results obtained by tuning various hyperparameters such as lag, number of layers, and number of neurons. GRU was found to be the better predictor in the studies with univariate data as compared to LSTM. ST	Low (92%)	Considering the single features from the dataset.
4	BL Gl., 2021[5]	Seasonal linear Quadratic and Multiple regression	Focused on STEF for non-residential buildings. ST ST	Low(92%)	It loses its ability to generalize effectively to new or unseen data.
5	Zhang et al., 2016 [6]	SVR GA PSO	Forecast the energy consumption of institutional buildings on a half-hourly ST and daily basis.	Low (86%)	Low MAPE for daily and half-hourly DSs compared GA and PSO optimization .
6	Amber et al., 2017 [7]	Regression Models	Predict the daily energy consumption of a building. ST	Low(87%)	Not address the model with new weights, and no accurate information for building occupancy.
7	Nikiforov et al 2019 [8]	RNN	Load prediction for large commercial buildings using RNNs. ST	High(96%)	Not considered all features in the dataset.
8	Chen et al., 2017 [9]	SVR	Forecast office buildings' electrical load and find demand response energy ST for office buildings.	Low (90%)	Did not consider residential buildings in all situations & considered only office buildings.
9	Li et al., 2020 [10]	Regression Models	compared classification and regression models for non-residential buildings' electricity and thermal load forecasting. LT	Low (92%)	Physical parameters of building's not yet considered for thermal and daily electricity forecasting.
10	Jihad et al., 2018 [11]	ANN	Predict energy load for residential buildings. ST	High (98%)	Considering only an individual climate zone for the energy prediction of the building.
11	Kim et al. 2019 [12]	ANN	Forecast the peak energy demand for non-residential buildings. ST	Low (85%)	Different models & different data for institutional buildings are not used.
12	Iqbal et al., 2021 [14]	ANN	Forecasting the energy consumption of SBs using ANN and the IoT. ST	High (95%)	Fails to give a good value of R^2, High error metrics in terms of MAE & RMSE are observed.

intricate temporal dependencies that are essential in dynamic and time-sensitive environments. Similarly, Jin Guohui et al. [28] used grey correlation analysis to forecast energy consumption by analyzing the relationships between various influencing factors. Though useful for understanding inter-variable patterns, this technique fails to account for the non-linear interactions and evolving dependencies often observed in real-world energy systems, limiting its practical application in complex settings.

R. Sevlian et al. [29] also discussed challenges in scalability when predicting energy consumption for small customer groups, pointing out the limitations of traditional statistical methods when applied to larger populations or more diverse building structures. To enhance predictive performance, Quilumba et al. [30] proposed a k-means clustering algorithm that yielded an 11% improvement in prediction accuracy. However, while clustering models like k-means can group similar data points, they struggle to model deeper patterns such as temporal correlations and nonlinear relationships between features.

In an effort to overcome these shortcomings, researchers began to integrate ML with more advanced ensemble and clustering strategies. Wang et al. [31] introduced an ensemble prediction system that combined hierarchical clustering with DL models to boost energy prediction performance. Although the ensemble approach improved accuracy, it introduced significant computational overhead and required substantial processing resources, making it less practical for real-time or large-scale applications. Likewise, Breiman et al. [32] applied the Random Forest algorithm to forecast energy usage across customer groups. This method offered a trade-off between performance and calibration efficiency, but as a classifier, Random Forest inherently lacks the capacity to capture time-based dependencies crucial for sequential prediction tasks in energy systems.

These limitations in both classical and ML methods laid the groundwork for the evolution toward DL-based approaches, which are designed to automatically capture non-linear relationships and temporal dynamics from raw data. Hybrid DL models such as CNN-LSTM, CNN-Bi-LSTM, CNN-GRU, TCN-RNN, TCN-LSTM shown promise in addressing many of the constraints seen in earlier methods, particularly in handling complex sequences and achieving higher predictive accuracy under diverse and realistic energy consumption scenarios.

2.2.2 Exploring Energy Prediction Models: Strengths, Drawbacks, and Future Directions

Accurately predicting how much energy a building will use isn't just a technical exercise it's key to making our energy systems more efficient and sustainable. Over time, researchers have developed different types of models to tackle this challenge.

The field has moved from traditional statistical approaches to ML, and more recently to DL, with each new method designed to address the limitations of those that came before.

In the early stages, most studies focused on statistical models, especially those using regression and time-series techniques. For example, Kim et al. [33] used LR to link energy use from plug loads with occupant counts in buildings. While this showed a decent correlation, it lacked the precision needed for complex scenarios. Mahdavi et al. [34] took it a step further by using a Weibull distribution to better estimate peak loads, and others like Amjady et al. [35] and Espinoza et al. [36] employed ARIMA models with promising results—sometimes achieving up to 90% accuracy in R^2 terms. However, these models had a major weakness: they assumed a fixed, linear relationship between variables. In real-world buildings, energy consumption is influenced by a variety of dynamic and non-linear factors—something these traditional models simply weren't built to handle.

Other studies highlighted more limitations. For instance, Ding et al. [37] used PIR sensors and a Markov model to estimate energy use based on occupancy, but left out critical environmental variables like temperature or weather. Likewise, research from Halidi et al. [38], Yun et al. [39], and Anand et al. [40] emphasized how factors like indoor climate and occupant behavior also play key roles, but these were often missing from purely statistical approaches.

To tackle these gaps, researchers began turning to ML. ML techniques, especially models like ANNs, are better at picking up on complex, non-linear relationships. Zuraimi et al. [41] and Ouf et al. [42], for instance, used ML to estimate occupancy based on CO_2 sensor data and showed that adding environmental variables helped improve predictions significantly.

A comprehensive review by Alzahrani et al. [43] pointed out that many ML-based EF models still tend to rely mainly on past energy usage, often missing out on more dynamic factors like building usage patterns or equipment efficiency. Ahmad et al. [44] applied ML for short- and medium-term forecasting with good results, but didn't address an important issue: how interpretable these models are. For building managers or policymakers, it's crucial to understand why a model makes a certain prediction. Meanwhile, ensemble approaches—like those proposed by Krishnan et al. [45] and Wang et al. [46]—helped boost accuracy by combining multiple ML models. But this came at a cost: high computational complexity and scalability issues, especially problematic for real-time applications.

Even though ML provided more flexibility than traditional methods, it still fell short in capturing temporal dependencies—the patterns that unfold over time in energy consumption. This is where DL made its entrance.

DL models such as RNNs, LSTM networks, and CNNs are particularly well-suited for time-series forecasting because they can identify both temporal and spatial patterns. Lu et al. [47] demonstrated the strength of LSTM networks in capturing LT energy trends. However, their model only used past energy usage and didn't consider external influences like occupancy or weather—two factors that significantly affect how energy is consumed in practice.

Recognizing this, researchers began to design hybrid and context-aware DL models. Markovic et al. [48], for example, included occupancy data in their LSTM-based forecasts, while Anand et al. [49] tested multiple ML techniques using institutional occupancy data. These efforts reflected a growing awareness that context—who is in the building, how it's being used, and the outside weather—matters a lot.

Still, DL comes with its own set of challenges. As highlighted by Ahmed et al. [44] and Paterakis et al. [50], interpretability remains a major issue. It's often difficult to understand why a DL model makes a certain prediction, which can hinder its real-world adoption—especially in regulated industries where explainability is critical. Additionally, DL models can be computationally intensive and may not be feasible for systems that require fast, lightweight predictions, as noted by Wang et al. and Krishnan et al.

To address these limitations, recent studies have proposed more balanced solutions. Hybrid models that combine CNN and Bi-LSTM architectures—like those explored in [51, 52]—have proven effective in capturing both spatial and temporal aspects of energy usage. Crucially, these models also incorporate occupancy and weather data, resulting in more accurate and practical predictions as shown in Table 2.2.

2.3 Current research in LT and occupancy-based energy prediction for SBs

Accurate forecasting of electricity demand plays a vital role in enabling smart EM and minimizing environmental impacts, particularly in SBs and grids. Over the years, the methods used for forecasting have evolved significantly — beginning with statistical techniques, moving into ML, and more recently embracing DL approaches. Each stage in this evolution has been driven by the need to address the limitations of previous methods while adapting to the increasing complexity of energy systems and the diversity of influencing factors.

The early phase of EF research leaned heavily on statistical approaches, such as regression models and time-series analysis. These methods offered a foundational framework to understand energy patterns using historical data. For instance, Mahdavi et al. [7] and Jamil et al. [8] applied regression analysis to model electricity usage in commercial and office buildings. Similarly, Atalay et al. [53] and Tang et al. [54] used regression techniques to identify consumption trends in residential and commercial sectors. While these methods were straightforward and interpretable, they were not without limitations. Many studies reported their inability to handle non-linear relationships, over-reliance on high-quality historical data, and limited adaptability to changing usage patterns or external conditions like weather or occupancy. For example, Malik et al. [4] noted how linear assumptions in ARIMA and regression models compromised accuracy, especially when faced with complex

Table 2.2: Summary of work related to occupancy-based energy in SBs

Sl No	Reference and Year	Models Used	ST or LT	Accuracy Low or High	Limitation
1	F. L. Quilumba et al. [51]	k-means	ST	High(95%)	Not able to capture more intricate patterns
2	Lu et al. 2018 [55]	LSTM	ST	Low(86%)	Did not consider occupancy count & external weather conditions. It limits the model's accuracy.
3	Ahmed et al. 2020 [63]	DL algorithms	Medium & LT	Low(86%)	Does not investigate the interpretability of the DL models.
4	Kim et al. 2017 [67]	Linear Regression	ST	Low(78%)	Limitation of this method is low in terms of accuracy.
5	Mahdavi et al. 2016 [68]	Weibull distribution	Medium & ST	High(96%)	occupancy are not considered
6	Kim et al. 2020 [75]	BR QNBP SCG LMBP	ST	Low(91%)	Recorded high error rates like 1.07- 2.23
7	Wang et al., 2023 [94]	LR ANN LSTM GBRT	ST	High (95%)	Not able to examine how regularly updating sample weights are influenced by validation sets.
8	Wei et al. 2019 [31]	ELM FFNN Ensemble	ST	High (93%)	Performance of 0.92% and 0.93% are recorded energy prediction with occupancy and without occupancy
9	Anand et al. 2021 [81]	SVR RF ANN-DNN ANN-FF, GB	LT	Low (79%- 85%)	MAE is very high.
10	Ouf et al. 2017 [83]	Statistical and Machine Learning	ST	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 [93]	GRU LSTM	ST	Low (79%)	Investigated and explored GRU-based prediction models to optimize energy is required for occupants' activities in SB.
12	Tsalikidi et al., 2024 [88]	ML ANN	ST	High (95%)	Getting more actual data from the real world helps them to make better guesses and be more dependable.

behaviors in electricity demand. Moreover, statistical models struggled with generalizability across different types of buildings or regions. As highlighted by Jamil et al. and Mahdavi et al., factors like seasonal variation, unpredictable consumer behavior, and weather fluctuations often led to reduced prediction reliability. Hernandez et al. [1] further emphasized challenges with model performance, data quality, and practical deployment when using traditional statistical approaches in real-world demand forecasting.

To overcome these drawbacks, researchers turned to ML, which introduced greater flexibility and the ability to learn complex, non-linear relationships from large DSs. ML models, such as Support Vector Machines (SVM), Random Forests (RF), and ANNs, demonstrated superior performance in recognizing patterns that statistical models failed to detect. Plageras et al. [6], for instance, applied ML techniques to forecast electricity usage based on historical data and key influencing variables, improving predictive accuracy. Memos et al. [3] used neural network predictive control in zero-energy buildings to optimize energy usage with real-time inputs. These models offered enhanced precision and adaptability, especially in environments with diverse data sources. However, ML approaches were not free from challenges. As noted by Alzahrani et al. [43] and Kim et al. [55], many ML models were complex, data-hungry, and prone to overfitting. Interpretability became another concern — while ML models could make highly accurate predictions, it was often difficult to understand the reasoning behind their outputs, which limited their practical application in real-world decision-making. Additionally, the inability of many ML methods to capture temporal dependencies — essential in time-series forecasting — left room for improvement. Lu et al. [5] echoed these concerns, identifying weaknesses in ML models in recognizing long-range dependencies and dealing with randomness in electricity demand. Han et al. [56] also noted the challenges of applying conventional methods in rapidly evolving energy systems where consumer behavior and environmental factors constantly change.

To bridge these gaps, researchers began employing DL approaches, which are particularly well-suited for modeling both temporal and spatial dependencies. Models like RNNs, LSTM networks, and CNNs offered powerful tools to model sequential patterns in electricity usage data. Lu et al. [47] and others demonstrated how DL models can capture long-range dependencies and adapt to the randomness in EC. These architectures excel in automatically extracting features and learning complex dependencies from raw data, making them particularly suitable for LT forecasting. Markovic et al. [48] and Anand et al. [49] went a step further by incorporating contextual features such as occupancy and environmental data into their LSTM-based models, improving prediction accuracy in real-world building environments. Despite their advantages, DL models are not without criticism. Studies like those by Ahmed et al. [44], Paterakis et al. [50], and Memos et al. [3] have pointed out issues such as poor interpretability, high computational costs, and sensitivity to data quality. These concerns make them harder to deploy in real-time or resource-constrained environments. Also, the "black-box" nature of DL makes it difficult for energy managers to justify or trust predictions without deeper insight into the model's workings. Wang et al. [46] and Krishnan et al. [45] also raised concerns about the scalability and computational overhead of ensemble and DL-based systems. Kim et al. [55] acknowledged the need for adaptive learning strategies to address these shortcomings.

To tackle these challenges, recent efforts have focused on developing hybrid DL frameworks that combine the strengths of multiple architectures. CNN-BiLSTM models, for example, have emerged as a powerful solution, offering the ability to capture both spatial and temporal features while incorporating external contextual inputs like occupancy and weather conditions [51, 52]. These models provide a more balanced and interpretable approach, addressing many of the limitations found in earlier statistical and ML methods. In doing so, they represent a promising direction for advancing electricity demand forecasting in smart building environments. The employed models, their corresponding references, and associated limitations are presented in Table 2.3. The above researcher has mainly focus on ST prediction, so we implemented data for the long term prediction.

Table 2.3: Summary of work related to extreme weather based on STEF

Sl No	Reference and Year	Models Used	LT or ST	Accuracy Low or High	Limitation
1	Hernandez et al. 2014 [54]	ARIMA SVR ANN	ST	Low(87%)	Dost not consider the impact of extreme weather on wind power on a multi level scale.
2	Moazami et al. 2019[81]	Statistical model	LT	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 [82]	StackLSTM BiLSTM CNN-LSTM ConvLSTM	ST	Low(90%)	Feature selection of data and preprocessing techniques are not done.
4	Watson et al. 2022 [83]	Regression methods	ST	Low(88%)	Limitation of this method is time complexity of the model high.
5	Yang et al 2023 [84]	BiLSTM GRU LSTM BP ELM	ST	High(96%)	The accuracy of the model less for large volume of data.
6	Kosovic et al 2020 [85]	Ensemble Statistical	ST	Low(91%)	High error metrics are recorded.
7	Guo et al 2020[86]	MINLP	ST	High(93%)	Limited to Short Circuit Faults(SCFs),
8	Tervo et al 2019 [87]	MLP	ST	Low (88%)	Data imbalance is high and for missing data they are using old basic techniques.
9	An et al 2020[88]	Adaboost PSO-ELM	ST	High (98%)	Training sample of the data are not selected based reconstruction.
10	Wang et al 2021 [89]	LSTM	ST	Low (83%)	Forecasting accuracy for various client categories are low.

2.4 Research Gap

2.4.1 Energy Optimization

Systems are designed to minimize energy usage while maintaining occupant comfort. ML and data models are used to predict energy loads accurately. Real-time energy use monitoring allows for the detection of optimization opportunities and enables adjustments to building operations. Smart building systems integrate technologies like sensors, controls, and automation to dynamically improve energy efficiency. SBs are instrumental in reducing costs, making them more sustainable, and enhancing operational effectiveness through optimized energy utilization. Using sophisticated monitoring and data analysis, SBs monitor energy usage in real time, enabling operators to spot trends, detect waste, and make specific enhancements. This forward-looking strategy sees energy used as efficiently as possible, minimizing waste and reducing costs.

One of the most important benefits of SBs is that they can adjust energy needs as they shift. Employing LTEF, they adjust heating, cooling, and lighting according to occupancy levels, weather, and peak hours. This adjusts not only to be more comfortable for users but also helps avoid wasted energy use.

Effective EM in SBs also aligns with larger environmental objectives. Through the reduction of energy wastage, such buildings contribute to carbon emission reduction, thereby supporting global sustainability initiatives. Optimized energy consumption also increases the resilience of building infrastructures, guaranteeing stable performance even during power fluctuations or severe weather conditions.

In addition to reducing costs and benefiting the environment, SBs enhance overall performance. Automated systems minimize the amount of manual adjustment, leaving resources available for other important tasks. With ongoing advancements in smart technology, the buildings are becoming increasingly efficient at conserving energy while performing at high levels.

In short, SBs provide a practical solution to the energy needs of today. They reduce operating expenses, facilitate environmentally friendly practices, and provide long term efficiency making them a smart option for the future of urbanization.

2.4.2 LTEF in SBs using AI, ML, and DL

SBs are transforming EM with AI, ML and DL technologies. These systems process enormous amounts of data to forecast and optimize energy consumption with incredible accuracy, making more efficient and sustainable buildings.

Underpinning this revolution are ML technologies such as regression models and decision trees. These technologies look back over past patterns of energy usage, determining correlations between variables such as time of day, occupancy, and weather. For instance, a regression model can learn that electricity demand jumps by 15% when it is above 30°C outdoors and alert the authorities ahead of time to make pre-emptive changes to cooling equipment.

Deep learning goes one step further with neural networks that can handle intricate, time series data. RNNs are especially useful because they can identify patterns in energy usage patterns, e.g., daily or weekly cycles. This enables very accurate STEP that take into consideration both normal patterns and anomalies.

AI fills in the gaps by reinforcement learning systems that constantly improve building operations. These algorithms run in real time, adjusting automatically HVAC settings, lighting levels, and other systems based on existing conditions and anticipated needs. For example, an AI system may pre-cool a building before a forecast heatwave, decreasing peak demand charges while keeping people comfortable.

2.4.3 Occupancy based LTEF in SBs

SBs are progressively implementing occupancy based EF for peak efficiency and minimization of wastage. Using IoT sensors and real time data analysis, the SBs predict near future energy usage accurately, according to the people present and what they do. ML algorithms, such as regression analysis and neural networks, analyze the input along with the context in the form of the time of day, trends of the past, and outside climatic conditions and create accurate predictions.

This method facilitates dynamic modulation of HVAC, lighting, and power systems to make sure that energy is utilized only when and where required. For instance, at low occupancy, the systems adjust automatically, while high usage elicits optimized action to sustain comfort without wasteful consumption. This leads to an elimination of 20–35% energy wastage, lower costs of operations, and better sustainability without diminishing occupant comfort.

Ongoing data monitoring enables these systems to learn and evolve over time, improving predictions and responses. When combined with larger building management platforms, occupancy based forecasting enables smarter decision making, from load balancing to predictive maintenance. Ultimately, this technology turns buildings into responsive, efficient ecosystems that match energy use to actual needs providing cost savings, environmental benefits, and reliable performance in an increasingly energy conscious world.

2.4.4 Federated and XAI in role in LTEF in SBs

Federated learning and explainable AI (XAI) play pivotal roles in enhancing energy consumption (EC) prediction in SBs. Federated learning enables decentralized data processing across multiple locations, allowing various SBs to collaboratively learn from their respective DSs without compromising privacy. This method enhances data security and compliance with regulations by keeping sensitive information on local devices while improving model robustness through collective knowledge sharing.

XAI complements federated learning by providing transparency and interpretability to complex predictive models. Techniques like LIME (Local Interpretable Model-agnostic Explanations) facilitate understanding of model predictions by highlighting the influence of individual features, such as temperature, occupancy, and HVAC operational data, on energy usage forecasts. This transparency is crucial for stakeholders, enabling them to trust and effectively utilize the model's insights for decision making.

Together, federated learning and XAI foster a more collaborative and insightful approach to EM. They empower building managers and occupants to make informed choices about energy usage, leading to optimized operational efficiency and enhanced sustainability. This dual approach not only addresses privacy concerns but also promotes a proactive stance in EM, crucial for addressing global energy challenges.

2.5 Research Plan

This study will be conducted in four sequential phases, each addressing critical aspects of EF in SBs:

2.5.1 LTEF Framework

Develop an innovative methodology for accurate LTE demand prediction in SBs, integrating advanced analytics and building operational data.

2.5.2 TCN-GRU Hybrid Model for Energy Storage Optimization

Develop and deploy an innovative hybrid forecasting framework that synergistically combines **TCN** and **Gated Recurrent Units (GRU)** to establish a robust correlation between occupant density patterns and energy demand fluctuations. This integrated architecture will be specifically optimized to enhance the efficiency of energy storage systems in SBs through precise, real time demand forecasting.

2.5.3 TCN-Bi-LSTM Hybrid Approach for Occupancy-Based Forecasting

This study proposes an advanced hybrid forecasting model that integrates **TCN** and **Bi-LSTM** to significantly improve the accuracy of LTE consumption predictions in SBs. The model specifically focuses on leveraging **occupancy pattern dynamics** as a key predictive feature.