Chapter 1

Introduction

This chapter presents the introduction on the energy management (EM) in section 1. Secondly we define the problems related to smart buildings (SBs) as well as ML in section 1.1. The third section defines in the scope of the work 1.2 and objective of the work in 1.3. Further we define the methodology 1.4 then significant contribution 1.5 and at, last organization of the chapters1.6

The effective management of electricity consumption (EC) in SBs has emerged as a critical challenge in modern energy systems, driven by the need for operational efficiency, cost reduction, and environmental sustainability. Buildings account for a significant portion of global energy usage, and optimizing their consumption patterns can lead to substantial economic and ecological benefits. Traditional forecasting methods, such as linear regression (LR) and time-series models, often fall short in capturing the intricate, nonlinear relationships and long-term dependencies (LTD) present in EC data. These limitations stem from the dynamic nature of energy usage, which is influenced by a multitude of factors, including occupancy patterns, weather conditions, equipment efficiency, and even real-time electricity pricing. To address these challenges, deep learning (DL) has emerged as a transformative approach, offering superior capabilities in modeling complex temporal and spatial patterns within large-scale energy datasets (DSs). [1–4]

Recent advancements in DL have demonstrated remarkable success in improving the accuracy of EC predictions. Unlike conventional methods, DL models can automatically extract high-level features from raw data, adapt to changing consumption trends, and handle multivariate inputs with minimal preprocessing. Techniques such as convolutional neural networks (CNNs) excel at identifying local patterns in energy data, while recurrent neural networks (RNNs) and their variants, including long short-term memory (LSTM) and gated recurrent units (GRUs), are particularly effective in modeling sequential dependencies over time. More recently, hybrid architectures that combine the strengths of different DL models have shown even greater promise in capturing both short-term fluctuations and LT trends in EC.

This study introduces an advanced DL framework designed to enhance hourly EC forecasting in SBs. The proposed approach leverages a multi-modal neural network architecture that integrates spatial, temporal, and contextual features from heterogeneous data sources, including IoT sensors, building management systems, and external environmental DSs. By employing attention mechanisms, the model can dynamically weigh the importance of different input variables, improving its ability to adapt to sudden changes in energy demand. Additionally, the framework incorporates transfer learning techniques to generalize across different building types, reducing the need for extensive retraining when deployed in new environments.

Accurate EC forecasting is not only crucial for operational efficiency but also plays a vital role in demand response strategies, grid stability, and renewable energy integration. For instance, precise predictions enable building operators to optimize Heating, Ventilation, and Air Conditioning (HVAC) scheduling, reduce peak demand charges, and participate in energy-saving incentive programs. Furthermore, by minimizing energy waste, DL-driven forecasting contributes to broader sustainability goals, helping organizations meet regulatory requirements and reduce their carbon footprint. [1, 5, 6] Beyond standalone prediction models, this research also explores the potential of federated learning for EC forecasting in distributed smart building networks. Federated learning allows multiple buildings to collaboratively train a shared DL model without exchanging raw data, thereby preserving privacy and security. This approach is particularly relevant for large-scale commercial and residential complexes where data sharing may be restricted due to regulatory or competitive concerns. [4, 7, 8]

In summary, this study highlights the transformative potential of DL in revolutionizing EC forecasting for SBs. By combining cutting-edge neural network architectures with real-world IoT data, the proposed framework aims to deliver more accurate, scalable, and adaptive EM solutions. The findings underscore the importance of AI-driven approaches in advancing smart city initiatives, energy conservation, and sustainable building operations, paving the way for a more efficient and environmentally responsible future.

1.1 Problem Formulation

In recent years, the rapid expansion of SBs and their integrated EM systems has opened new avenues for the application of advanced intelligent techniques, such as machine learning (ML) and artificial intelligence (AI), to optimize energy consumption. These technologies hold significant potential to enhance energy efficiency, reduce costs, and improve sustainability in building operations. However, existing state-of-the-art approaches face considerable limitations in accurately predicting and controlling energy usage. These challenges stem from the inherent complexity of building systems, which involve dynamic interactions between various components, as well as the massive volumes of data generated by these systems. As a result, there is a pressing need to explore and develop innovative intelligent techniques tailored for smart building EM. Such solutions must be capable of addressing these complexities while delivering cost-effective, efficient, and scalable outcomes.

This thesis seeks to tackle these challenges by investigating, implementing, and proposing novel methods and models for smart building EM. Specifically, it focuses on leveraging DL-based approaches, which have shown promise in handling complex, high-dimensional data and uncovering patterns that traditional methods may overlook. The research also includes a comparative analysis of these DL-based methods with existing techniques, aiming to demonstrate their effectiveness, efficiency, and scalability in real-world applications. Through this work, the thesis aims to contribute to the development of advanced EM solutions that can meet the growing demands of SBs.

1.2 Scope of the work

This study creates a smarter way to predict electricity use in modern buildings hour by hour. Buildings today are packed with sensors and smart systems that generate tons of data - from AC usage to occupancy counts. We've developed new methods to make sense of all this information, even when the data has gaps or inconsistencies.

Our approach does something special: it can spot both the quick changes (like when everyone turns on lights at once) and LT patterns (like seasonal heating needs). We tested it across different buildings - offices, schools and apartments - and found it outperforms traditional prediction methods, especially when dealing with unexpected demand spikes or changing seasons.

What makes this really practical is that we've designed it to work in real-world situations. It's fast enough for live decision-making and can scale up for entire networks of buildings. Facility managers can use these predictions to better control heating/cooling systems, participate in energy savings programs, and integrate renewable power more effectively.

The system is built to grow smarter over time too - it can easily incorporate new data like ultra-precise weather reports or real-time equipment status. In real terms, this could help typical buildings cut energy waste by 15-20%, which adds up to significant cost savings and environmental benefits as more buildings adopt smart technologies.

Ultimately, we're bridging the gap between complex energy math and practical tools that building operators can actually use to save money and reduce their carbon footprint.

1.3 Objective

The key objectives aligned with the problem formulation are as follows:

1. Establish comprehensive datasets capturing operational and energy consumption patterns under varying environmental and usage conditions.
2. Develop advanced feature selection methodologies to identify the most relevant and discriminative patterns in system performance data.
3. Enhance predictive capabilities for accurate and efficient energy usage forecasting using computational intelligence techniques.
4. Design novel hybrid analytical approaches for modeling and processing temporal dependencies in energy consumption data.
5. Implement optimization frameworks to improve the accuracy, reliability, and robustness of predictive systems.
6. Conduct extensive experimental validation comparing proposed techniques with existing conventional models using real-world datasets.
7. Demonstrate superior performance in recognizing complex temporal and spatial relationships within energy system data.
8. Develop practical implementations for intelligent energy management and automated decision-support systems.

9. Evaluate the adaptability and scalability of the proposed models across diverse operational environments and building types.

10. Promote sustainable and energy-efficient operations through improved reliability and optimized utilization of building resources.

1.4 Methodology

In this section, we proposed framework in figure 1.1 for accurate EC forecasting adopts a hybrid DL approach that combines sequence modeling with temporal pattern recognition. It is structured into three main stages: Data Acquisition, where raw sensor and contextual information are collected; Feature Extraction and Selection, where relevant patterns and influential factors are identified; and Energy Prediction, where the refined data is used to generate precise consumption forecasts.

Data Collection and Preprocessing The initial step involves gathering comprehensive DSs, including environmental parameters (temperature, humidity, daylight), occupancy metrics, and EC readings through sensors installed across the building. Missing or null data points are handled by filling them with mean values specific to each room, ensuring data completeness. Additionally, normalization techniques are applied to bring all features to a common scale, facilitating effective model training. The dataset is resampled to hourly intervals to capture the ST and LT patterns in energy usage.

Feature Extraction and Selection Effective feature engineering is crucial for model performance. Techniques such as statistical analysis and dimensionality reduction are employed to extract multi-scale temporal features that encode high- and low-frequency information within the data. These features include various time-based indicators (e.g., weekdays, weekends, holidays), occupancy levels, and environmental conditions, which significantly influence energy consumption. Feature

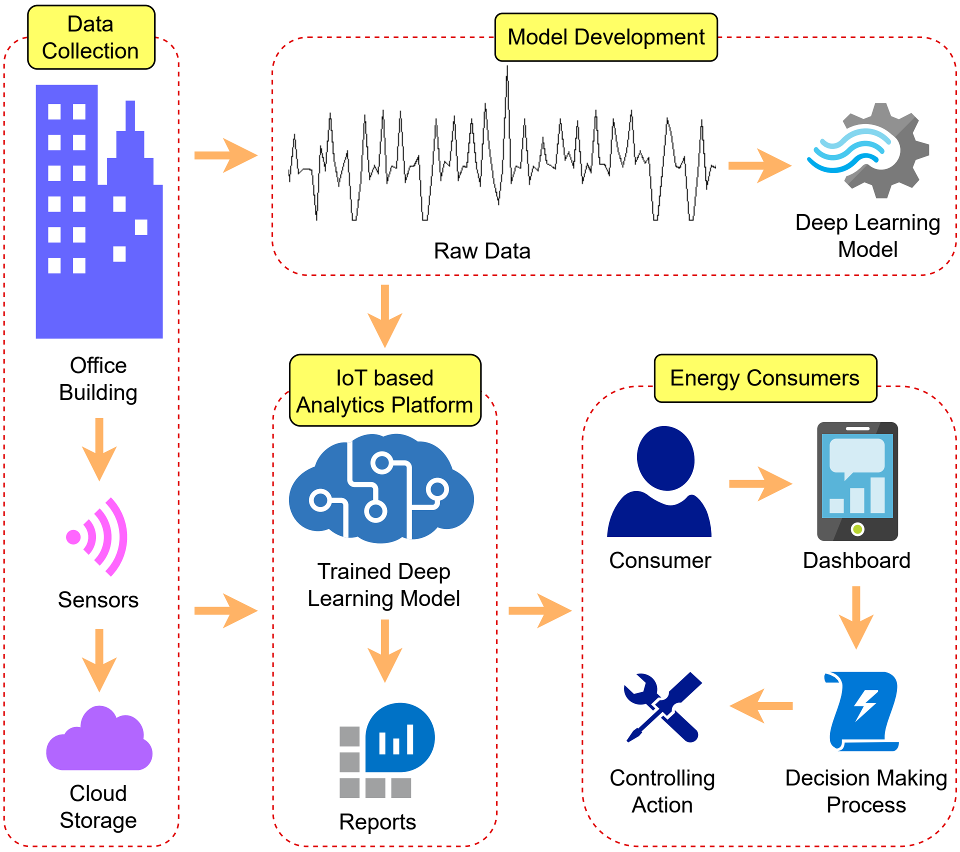

FIGURE 1.1: Architectural overview of proposed system.

selection processes are used to retain only the most relevant variables, improving the efficiency and predictive capacity of the subsequent models.

Model Prediction The proposed approach is carried out in two main stages: training and testing. During the training phase, a feature matrix X is used, where each row represents a distinct instance of training data containing relevant input features. Corresponding to each instance in X, there is an output value in the target vector Y, which represents the expected energy consumption prediction. The model is trained by learning the relationship between X and Y, allowing it to understand patterns in energy usage. Once trained, the model moves to the testing phase, where it applies this learned knowledge to new, unseen data in order to accurately predict energy consumption under various scenarios.

1.5 Significant Contribution

Significant Contributions of this Work

1. Development of novel hybrid DL models

   Introduced two hybrid architectures combining Temporal Convolutional Networks (TCNs) with GRU and Bi-directional Bi-LSTM respectively, for multivariate EC forecasting. These models are designed to capture both short and long term temporal dependencies and high/low-frequency patterns in smart building environments.

2. Advanced feature extraction

   Leveraged the strength of TCN in identifying diverse temporal structures and multi-scale frequency patterns, leading to more meaningful representations of complex energy usage behavior.

3. Federated learning architecture for privacy-preserving modeling

   Designed and implemented a federated learning framework to utilize distributed data from multiple building wings or zones, ensuring data privacy, improving scalability, and maintaining robust model performance in decentralized smart building setups.

4. Enhanced forecasting accuracy

   Demonstrated superior prediction performance over traditional and ML models, validated through lower Mean absolute error (MAE), root mean square error (RMSE) and higher R^2 scores, particularly under nonlinear, multimodal, and noisy data conditions.

5. Incorporation of explainable AI (XAI)

   Applied LIME (Local Interpretable Model- agnostic Explanations) to enhance interpretability, offering transparent insights into how various input features—such as occupancy, temperature, and device usage—impact energy consumption predictions.

6. Effective modeling of complex and stochastic patterns

   Successfully addressed the nonlinear, dynamic, and uncertain nature of energy consumption data, accounting for environmental conditions, occupant behavior, and appliance-level variations.

7. Practical impact on smart building EM

   Provided a data-driven, real-time forecasting tool that enables cost savings, operational efficiency, and energy-aware decision-making, supporting sustainability goals and intelligent energy use in modern building systems.

8. Flexible and scalable framework for future research

   Established a modular and adaptable approach that can be extended across varied geographic regions, climatic zones, and additional contextual variables, offering a strong foundation for future smart EM research.

1.6 Organization of the Thesis

The overall structure of the thesis is illustrated in Figure 1.2. This dissertation comprises four contributing chapters, each described briefly below:
Chapter 2: This chapter provides an overview of state-of-the-art techniques presented in recent published papers.

Chapter 3: This chapter presents a smart building energy prediction strategy utilizing state-of-the-art techniques. The proposed model is evaluated against various ML, statistical, and DL models in terms of performance. A key contribution of this chapter is the introduction of a novel hybrid DL model based on TCN-GRU for forecasting smart building energy consumption. The model is analyzed for LT forecasting using two RNN variants: TCN and GRU. To assess its effectiveness,

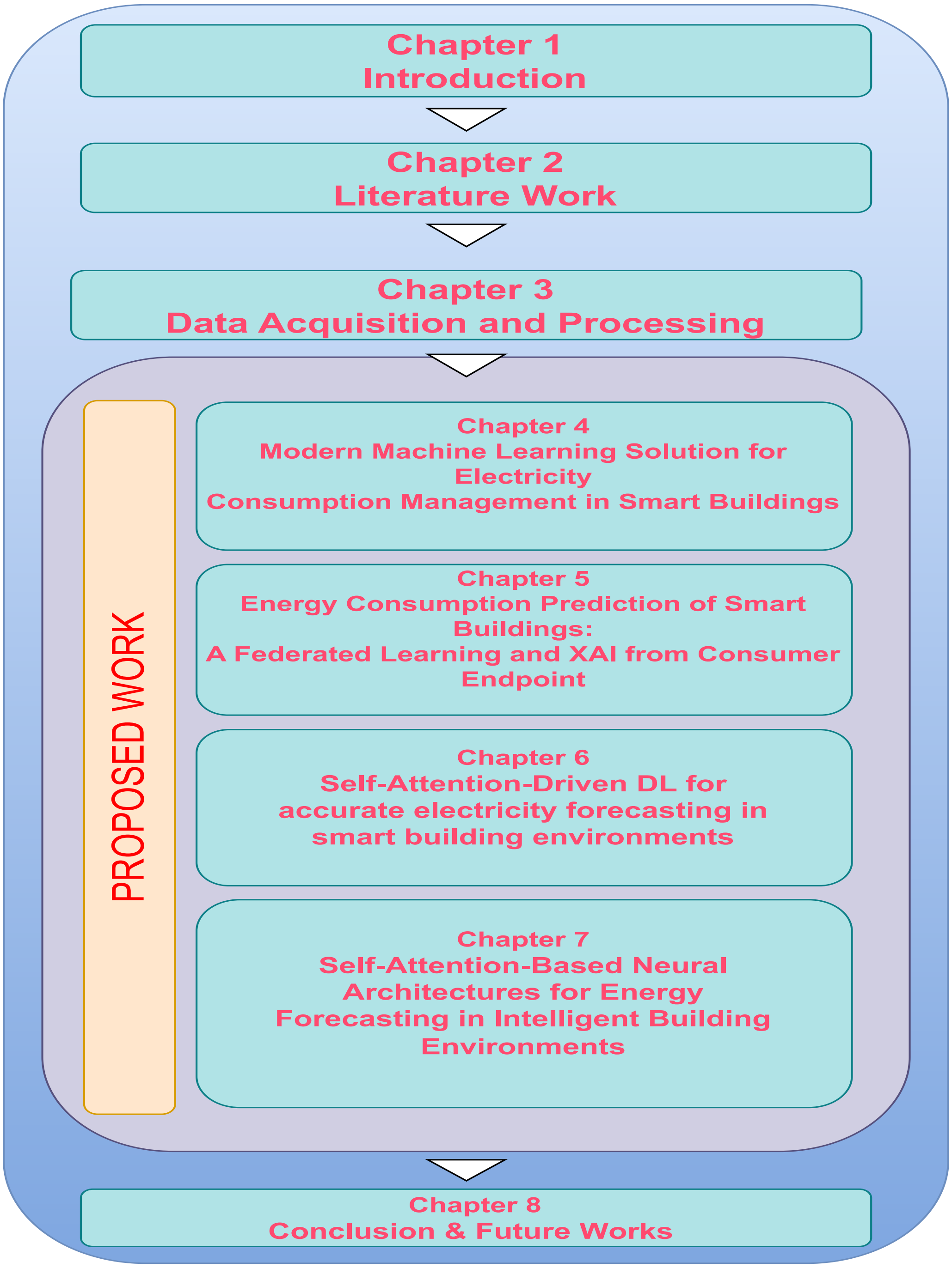

FIGURE 1.2: Layout of the Thesis

the proposed model is tested on a publicly available dataset and compared with alternative approaches using error metrics such as MAE, RMSE, and R^2 Score.

Chapter 4: This chapter introduce an innovative DL approach for energy consumption (EC) prediction, specifically tailored for SBs. Our model utilizes a federated learning architecture to effectively capture both low- and high-level information patterns within multivariate time series data from different sections of a smart building. To address the nonlinear and dynamic nature of this data, we integrate TCN and Bi-LSTM networks. TCN extracts various trends from the data, while Bi-LSTM learns these trends over time.

As a result, we propose a federated learning framework that leverages both TCN and Bi-LSTM for shared feature representation learning in multivariate time series data related to EC. To validate our approach, we conduct extensive evaluations using a dataset from an office building in Berkeley, California. Experimental results demonstrate that our model achieves high accuracy in EC prediction. To evaluate its performance, the proposed model is tested on a publicly available dataset and benchmarked against alternative approaches using error metrics including MAE, RMSE, and R^2 Score.

Chapter 5: In this chapter,the proposed method is inspired by the hybrid model (HM) explored in related studies and leverages the unique characteristics of the EC dataset. The objective is to effectively utilize high-level feature information (HLFI) to enhance EC prediction accuracy. To achieve this, we introduce a hybrid model that integrates TCN with GRU using a SA layer, referred to as TCN-Self Attention-GRU (TCN-SA-GRU).The incorporation of the SA mechanism enhances the model's ability to effectively capture and address data periodicity. This approach employs TCN for feature extraction and GRU for modeling LTD, leveraging the strengths of both components.At last, the performance is measured by MAE, RMSE, and R^2 Score.

Chapter 6: This chapter introduces the proposed method, inspired by the hybrid model (HM) explored in related studies and tailored to the unique characteristics of the EC dataset. The primary objective is to effectively utilize HLFI to enhance the accuracy of energy consumption prediction. To achieve this, we propose a hybrid model that integrates a Temporal Convolutional Network (TCN) with a Gated Recurrent Unit (GRU) and incorporates a Self-Attention (SA) layer, referred to as TCN-Self Attention-GRU (TCN-SA-GRU). In this framework, the SA-GRU functions as the local model, while the TCN serves as the global model, together forming a federated learning architecture. The inclusion of the SA mechanism strengthens the model's capability to capture and interpret data periodicity more effectively. In this approach, the TCN is employed for feature extraction, whereas the GRU captures long-term dependencies, leveraging the complementary strengths of both modules. Finally, the model's performance is evaluated using MAE, RMSE, and R^2 score.

Chapter 7: This chapter presents a proposed method inspired by the hybrid model (HM) explored in related studies, utilizing the unique characteristics of the EC dataset. The goal is to effectively harness HLFI to improve the accuracy of EC prediction. To achieve this, we propose a hybrid model that combines TCN with Bi-LSTM and incorporates a SA layer, referred to as TCN-Self Attention-Bi-LSTM (TCN-SA-Bi-LSTM). The SA-Bi-LSTM method is implemented as a local model and TCN as a global model, combined making a federated learning framework. The integration of the SA mechanism enhances the model's ability to capture and address data periodicity more effectively. In this approach, TCN is used for feature extraction, while GRU models LTD, leveraging the strengths of both components.At last, the performance is measured by MAE, RMSE, and R^2 Score.

Chapter 8: This thesis explores the use of machine learning and deep learning methods—such as LR, ARIMA, RNN, LSTM, Bi-LSTM, TCN, and GRU—for short-and long-term energy forecasting in smart buildings. It proposes hybrid deep learning models, notably TCN-SA-GRU and TCN-SA-Bi-LSTM, which combine convolutional, self-attention, and recurrent mechanisms to improve prediction accuracy and efficiency. Trained on real-world datasets from Berkeley and Vienna, these models outperform traditional approaches, achieving lower MAE and RMSE and higher R^2 values.

1.7 Proposed model Novelty

- The proposed hybrid model, TCN-SA-Bi-LSTM, introduces a novel integration of Temporal Convolutional Networks, Self-Attention, and Bi-LSTM layers within a federated learning framework. This combination effectively captures multi-scale temporal patterns, emphasizes critical features, and models long-term dependencies, resulting in enhanced forecasting accuracy, robustness, and data privacy for smart building energy prediction

- The proposed model is novel because it integrates Temporal Convolutional Networks and Gated Recurrent Units, enabling accurate electricity consumption predictions in smart buildings by capturing both high- and low-frequency patterns and long-term dependencies, which outperforms conventional and existing deep learning models in prediction accuracy and efficiency.

- The proposed TCN-SA-GRU model introduces a novel hybrid architecture integrating Temporal Convolutional Networks with self-attention mechanisms and GRUs, enabling enhanced feature extraction and focus on critical time points. This combination improves long-term forecasting accuracy, adaptability to complex multivariate data, and real-time energy management in smart building environments.

The research contributes by: (1) introducing a robust framework for long-term energy forecasting using multi-scale convolutions and attention mechanisms; (2) applying federated learning to preserve data privacy; and (3) using explainable AI tools like LIME to reveal key energy drivers. Practical outcomes include enhanced load management, cost savings, and reduced emissions, while future directions involve integrating contextual features, enabling real-time edge deployment, and expanding datasets for broader applicability.