GSJ: Volume 12, Issue 7, July 2024, Online: ISSN 2320-9186
www.globalscientificjournal.com

Load Prediction of HVAC Systems using Deep Learning

[1]MD TUHINUR RAHMAN, [2]S M SOJIB AHAMED, [3]HOSSAIN IMRAN, [4]MD NADIRUZZAMAN NAHID, [5]ISLAM SARAL

[1]Southwest University of Science and Technology, China; [2]Nanjing University of aeronautic and astronauts, China; [3]North China Electric Power University, China; [4]North China Electric Power University, China; [5]North China Electric Power University, China

ABSTRACT

Currently, electricity is of utmost importance to the progress of a country's economy and society. The relentless surge in energy demand from modern buildings poses a profound challenge to global primary energy consumption, exhibiting an unwavering upward trajectory. This study constitutes a pivotal effort directed at fortifying energy efficiency by precision-focused short-term load prognostication for Heating, Ventilation, and Air-Conditioning (HVAC) systems. Within this study, a cutting-edge methodology unfolds through the synergistic amalgamation of Restricted Boltzmann Machines (RBM) and Artificial Neural Networks (ANN). This integration unfolds a trans-formative process, initiating with RBM pre-training on input data to autonomously unravel intricate hierarchical features. Serving as a potent feature extractor, the RBMs learned features seamlessly interlace with the original input, engendering a harmonized set. Subsequently, this amalgamated set propels the training of the ANN, harnessing the synergistic prowess of RBMs unsupervised learning and ANNs nonlinear mapping acumen. The resultant amalgamation begets a robust and adaptive model, poised to elevate precision in HVAC system load predictions. A rigorous evaluation

tuhinurrahmantuhin1996@gmail.com; smsojibahmed@gmail.com; imranme27@outlook.com; nadiruzzaman.nahid77@gmail.com; islamsaral@ncepu.edu.cn

substantiates the model's efficacy, unveiling a strikingly low Mean Absolute Error (MAE) of 0.1541, a minimal Mean Squared Error (MSE) of 0.3405, a diminutive Root Mean Squared Error (RMSE) of 0.5835, and an impeccable R-squared (R^2) value of 1. This fusion propels advancements in predictive accuracy, poised to make a significant impact in the realm of energy-efficient HVAC system management. Furthermore, the suggested approach has significant adaptability and can be employed in several additional applications involving the prediction of energy system load.

Keyword: HVAC System, Load Predictions, Deep Learning, RBMs, ANNs, Model Interactions.

GSJ: Volume 12, Issue 7, July 2024
ISSN 2320-9186

Table of Contents

List of Figures

List of Tables

CHAPTER 1 Introduction

1.1 Overview

Heating, ventilation, and air conditioning (HVAC) systems play a crucial role in maintaining thermal comfort and indoor air quality in various buildings, ranging from residential homes to commercial establishments [1]. Efficient operation of HVAC systems is essential for optimizing energy consumption and minimizing environmental impact. However, accurately predicting HVAC system load is a challenging task due to the complex inter-actions between various factors such as weather conditions, building characteristics, and occupant behavior [2-3]. In the intricate tapestry of modern architecture and building management, Heating, Ventilation, and Air Conditioning systems emerge as linchpins, orchestrating the delicate dance of thermal comfort and indoor air quality. From the snug confines of residential abodes to the sprawling spaces of commercial establishments, the ubiquity of HVAC systems underscores their pivotal role in shaping the environments we inhabit. Beyond mere creature comforts, these systems wield a profound influence on energy consumption and environmental impact, making their efficient operation an imperative for sustainable building practices. HVAC systems operate at the nexus of technological sophistication and human well-being, tasked with the mission of maintaining optimal thermal conditions and air quality within diverse structures. Residential homes, with their distinct requirements for comfort, stand alongside commercial establishments where HVAC systems cater to the diverse needs of occupants and the demands of various activities. In this nuanced context, the efficiency of HVAC systems becomes paramount, not merely as a measure of energy conservation but as a linchpin for environmental stewardship. The delicate balance between ensuring comfort and minimizing ecological footprint necessitates a profound understanding of HVAC operations, particularly in the realm of load prediction. Accurately predicting HVAC system load is a formidable challenge, an intricate puzzle governed by the dynamic interplay of numerous variables. Weather conditions, with their capricious shifts, exert a profound influence on the thermal demands placed on HVAC systems. The unique characteristics of the building itself, from its architectural design to the materials used, further complicate the prediction task. Moreover, the unpredictable element of human behavior, manifested in occupancy patterns and individual preferences, adds an additional layer of complexity. It is within this labyrinth of interactions that the quest for precision in HVAC system load prediction takes center stage. The significance of this challenge is underscored by the ripple effects it carries. Inefficiencies in predicting HVAC system loads result in sub-optimal performance, translating into unnecessary energy consumption and, consequently, an enlarged carbon footprint [4]. As global initiatives intensify to combat climate change, the role of HVAC systems in sustainable building practices becomes increasingly critical [5]. Therefore, is not merely to surmount the challenges of load prediction but to leverage technological advancements in a manner that aligns HVAC operations with the ethos environment responsibility.

Around the world, almost 40% of total energy consumption is attributed to buildings, with HVAC systems accounting for 40-60% of that energy usage [6]. As the world strives to address the challenges of energy consumption in buildings, optimizing HVAC systems has become a critical priority. Modern buildings are increasingly adopting energy-efficient appliances and cutting-edge technologies, paving the way for a future of sustainable energy supply management and fault detection mechanisms. While traditional regression analysis has limitations in accurately predicting the dynamic characteristics of HVAC load data, this study presents a groundbreaking approach [7-9].Despite these multifaceted considerations within this thesis, we propose an deep learning based approach to HVAC system load prediction by integrating Restricted Boltzmann Machines(RBMs) and Artificial Neural Networks (ANNs). This pioneering methodology aims to surmount the intricacies posed by unpredictable variables such as weather conditions, building characteristics, and occupant behavior. The ANNs offers a robust framework for capturing complex relationships within the data, while the RBMs enhances feature learning, optimizing the system’s adaptability. By synthesizing these advanced technologies, our approach seeks to transcend traditional limitations in load prediction, fostering precision and efficiency. This integration not only represents a significant contribution to the field but also exemplifies a tangible step towards the practical application of cutting-edge technologies in the pursuit of sustainable and energy-efficient HVAC system management. As we delve into the subsequent chapters, the intricate architecture and interactions of the ANNs and RBMs models will be explored, providing a comprehensive understanding of their role in revolutionizing load prediction methodologies for HVAC systems.

-

1.2 **Motivation**

Deep learning models have emerged as a powerful tool for predicting HVAC system loads, offering significant advantages over traditional methods. These models excel at capturing complex nonlinearities and adapting to dynamic environments, leading to improved prediction accuracy, energy efficiency, proactive maintenance, enhanced system reliability, and ensured occupant comfort. Advancements in computational power and data accessibility have increased the feasibility of real world implementation, accelerating re-search and development efforts in this domain. My motivation for this study is to create an accurate HVAC system load prediction model using deep learning. The potential of unsupervised RBMs feature extraction combined with the prediction power of ANNs on short-time HVAC system data is promising. This ongoing research holds immense potential for creating intelligent and energy-efficient building management systems, paving the way for a more sustainable future.

1.3 **Problem Statement**

The effective operation of HVAC systems faces a substantial challenge due to the inadequacies of current load prediction methods. These methods often rely on simplistic models that fall short in capturing the complex and short-term dynamics of buildings. This thesis aims to address a critical gap in our understanding by exploring how Deep Learning (DL) can revolutionize HVAC load predictions through the development and evaluation of advanced models. The key challenges include modeling the intricate dynamics of buildings, ensuring the availability and quality of diverse datasets, investigating short-term adaptability, and enhancing the interpret-ability of DL models. The overarching goal is to contribute significantly to the improvement of accuracy and adaptability in HVAC load predictions, thereby facilitating the development of energy-efficient building management strategies.

1.4 Aims and Objective

The primary objective of this research is to introduce a RBMs-ANNs integrated load prediction method for HVAC systems. To achieve this overarching goal, we systematically address the following specific objectives:

1. Analyze the advantages and disadvantages of RBMs and ANNs in the context of HVAC system load prediction.
2. Develop a new prediction method by integrating the strengths of RBMs and ANNs to enhance accuracy and efficiency.
3. Validate the proposed method through comprehensive comparisons with RBMs, ANNs methods, utilizing realistic data collected from industries.
4. Investigate the potential of the presented method to contribute to optimized power consumption design and planning for HVAC systems.
5. Improve energy efficiency and occupant comfort by optimizing HVAC operation based on the developed load prediction model.
6. Contribute valuable insights to the advancement of HVAC system control strategies and the broader development of energy management strategies in large-scale commercial buildings.

This research aims to address the specified subjects sequentially, providing a comprehensive exploration of the integrated RBMs-ANNs approach for HVAC system load prediction and its practical implications.

1.5 Organization of this Thesis

The thesis is organized into five chapters that systematically guide the reader through the research process. Chapter 1 provides an introduction to HVAC load prediction, high-lighting its importance and the challenges it poses. Chapter 2 delves into the background of HVAC systems and load prediction, reviewing existing literature and identifying re-search gaps. Chapter 3 presents the proposed hybrid deep learning model, detailing its components, data pre-processing procedures, and training process. Chapter 4 presents the experimental setup, results. Finally, Chapter 5 summarizes the conclusion summary, discusses the limitations, and suggests directions for future work.

The introduction section of this thesis delves into the significance of accurate HVAC system load prediction in optimizing energy consumption and minimizing environmental impact. It highlights the challenges associated with traditional load prediction methods, particularly regression analysis, in capturing the dynamic characteristics of HVAC load data.

The section introduces a groundbreaking approach that integrates Artificial Neural Networks and Restricted Boltzmann Machines to surmount these challenges. The motivation for this research stems from the global imperative to address the substantial energy consumption attributed to HVAC systems and the need for advanced load prediction methodologies for modern buildings. The problem definition clearly outlines the criticality of accurate short-term load prediction for large-scale commercial buildings and the inadequacy of traditional regression analysis methods. Finally, the section presents the aims and objectives of the research, which focus on developing a highly accurate and robust deep learning model for HVAC load prediction and contributing to the advancement of HVAC system control and energy management strategies.

CHAPTER 2 Background And Literature Review

2.1 Background

Heating, Ventilation, and Air Conditioning (HVAC) systems, akin to invisible choreographers of comfort, orchestrate ideal indoor environments, seamlessly balancing temperature and optimizing energy usage across diverse settings such as homes, offices, and industrial spaces [10]. As societies continue to urbanize and the demand for energy-efficient buildings rises, the importance of efficient HVAC system operation becomes increasingly evident. The effective management of HVAC systems involves predicting and regulating the system load, which refers to the amount of heating or cooling required to maintain the desired indoor conditions [11].

Traditionally, load prediction in HVAC systems has been approached using rule-based methods and mathematical models that rely on predefined equations [12-14]. However, these methods often struggle to adapt to the dynamic and nonlinear nature of building environments, leading to sub-optimal energy utilization and comfort levels. As a response to these challenges, the emergence of deep learning techniques has provided a promising avenue for more accurate and adaptive load predictions.

Deep learning, a subset of machine learning, leverages artificial neural networks to automatically learn and extract hierarchical representations from data [15]. This approach has demonstrated remarkable success in various fields, including image recognition, natural language processing, and speech recognition [16-18]. The application of deep learning in the domain of HVAC systems introduces an innovative paradigm shift [19-20], enabling the development of models that can autonomously discover intricate pat-terns and dependencies within the data.

The utilization of deep learning in load prediction for HVAC systems brings several advantages. Firstly, these models can adapt to diverse and dynamic building conditions, providing a more responsive and accurate prediction of the system load. Secondly, the ability of deep learning models to process large-scale and complex datasets allows for a comprehensive analysis of factors influencing HVAC performance, including external weather conditions, occupant behavior, and system characteristics. Thirdly, the auto-mated feature learning capability of deep learning mitigates the need for explicit feature engineering, potentially reducing the burden of model development and enhancing scalability [21].

Despite the promise of deep learning, the field of load prediction for HVAC systems using these techniques is still in its infancy. Current research efforts have begun exploring various neural network architectures, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), to capture temporal dependencies in the data

Additionally, attention mechanisms and ensemble learning approaches are being investigated to enhance the interpretability and robustness of predictions [23].

This thesis contributes to the growing body of knowledge in the intersection of HVAC systems and deep learning by addressing several critical aspects. Firstly, it delves into the existing literature on load prediction methods in HVAC systems, highlighting the limitations of traditional approaches and the potential benefits offered by deep learning. Secondly, it proposes novel deep learning architectures tailored to the intricacies of HVAC load prediction, aiming to improve accuracy and adaptability. Thirdly, the research investigates the impact of various input features, including weather data, occupancy patterns, and building characteristics, on the performance of deep learning models.

The overarching goal of this research is to advance the understanding and application of deep learning techniques in the domain of HVAC system load prediction. By doing so, the thesis aims to contribute practical insights and methodologies that can be leveraged by building operators, energy managers, and researchers to enhance the efficiency, sustain-ability, and comfort of indoor environments. As the global focus on sustainable practices intensifies, the integration of advanced technologies like deep learning into HVAC systems becomes not only an academic pursuit but a crucial step towards a more energy-efficient and environmentally.

2.2 HVAC System and Load Prediction

In the modern architectural landscape, Heating, Ventilation, and Air Conditioning (HVAC) systems stand as unsung heroes, diligently orchestrating the symphony of thermal com-fort and indoor air quality [24]. From the cozy confines of residential dwellings to the sprawling spaces of commercial establishments and industrial facilities, HVAC systems orchestrate a delicate balance between energy efficiency, occupant well-being, and environmental stewardship. At the heart of this intricate dance lies the concept of HVAC system load, a multifaceted measure of the energy demand placed upon these systems to maintain desired indoor conditions.

The load on an HVAC system is a dynamic entity [25], shaped by a complex interplay of external and internal factors. Prevailing weather conditions, including ambient temperature, humidity, and solar radiation, exert a profound influence on the thermal demands placed upon the system. The intrinsic characteristics of the building itself, from its architectural design to the materials employed in its construction, further complicate the load prediction task. Moreover, the unpredictable element of human behavior, manifested in occupancy patterns and individual preferences, adds an additional layer of complexity.

Traditional load prediction methods [26], often relying on statistical models and rule-based systems [12-13], have struggled to capture the intricate dynamics and complex nonlinear relationships that govern HVAC system operation. These limitations have resulted in sub-optimal load forecasting, leading to inefficient energy usage and compromised occupant comfort. In contrast, deep learning approaches have emerged as a beacon of hope, offering a promising avenue for accurate and efficient load forecasting.

Deep learning algorithms, empowered by artificial neural networks (ANNs) and re-current neural networks (RNNs) [27], possess an uncanny ability to handle vast amounts of data, extract meaningful insights, and discern patterns that are invisible to the human eye. These algorithms excel at automatically extracting relevant features from raw data, effectively modeling time series patterns, and capturing intricate nonlinear relationships between various influencing factors. As a result, deep learning has emerged as a trans-formative force in HVAC load prediction, paving the way for a future of enhanced energy efficiency, improved occupant satisfaction, and sustainable building operations.

Deep learning's transformative impact on HVAC load prediction stems from its ability to overcome the inherent limitations of traditional methods. Unlike statistical models and rule-based systems, deep learning algorithms do not require explicit feature engineering, a tedious and often error-prone process. Instead, they automatically learn relevant features from the data itself, adapting to the nuances of the specific application. Furthermore, deep learning algorithms excel at handling time series data, a crucial aspect of HVAC load prediction. RNNs, in particular, are designed to capture temporal dependencies and long-range patterns, making them well suited for forecasting future load demands.

The benefits of deep learning for HVAC load prediction extend beyond its ability to capture complex dynamics and nonlinear relationships. Deep learning algorithms are also highly versatile, capable of incorporating diverse data sources, such as weather forecasts, building blueprints, and occupant behavior patterns. This wealth of information allows for a more comprehensive understanding of the factors influencing HVAC load, leading to more accurate and reliable predictions.

The advent of deep learning has ushered in a new era of HVAC load prediction, one characterized by enhanced accuracy, efficiency, and versatility. Deep learning algorithms have overcome the inherent limitations of traditional methods, enabling the capture of complex dynamics, nonlinear relationships, and a broader range of influencing factors. As deep learning continues to evolve, its impact on HVAC load prediction will only intensify, paving the way for a future of sustainable energy management, occupant comfort, and environmental stewardship.

2.3 **Research Gaps in HVAC System Load Predictions**

Despite significant advancements in HVAC load prediction methods, several research gaps remain unaddressed [28-29]. These gaps encompass data acquisition and pre-processing,

model development and evaluation, real-time prediction and implementation, specific applications and domains, and human-AI collaboration and explainability. Enhancing data granularity, improving data quality, and integrating diverse data sources are crucial for accurate predictions. Effective feature engineering techniques and balancing model complexity with interpretability are essential for model development. Real-time data processing, model adaptation, and integration with building automation systems are critical for real-time prediction and implementation. Developing load prediction models specifically tailored to large-scale commercial buildings, incorporating renewable energy sources, and enabling HVAC systems to participate in demand response programs are crucial for specific applications and domains. Human-in-the-loop systems, explainable AI, and incorporating domain knowledge into deep learning models can enhance decision-making, build trust, and improve model accuracy and interpretability. Addressing these research gaps will further advance the field of HVAC load prediction, leading to more accurate, efficient, and reliable models for optimizing energy consumption, enhancing occupant comfort, and promoting sustainable building practices.

2.4 **Literature Review**

Predicting Heating, Ventilation, and Air Conditioning (HVAC) system loads holds paramount importance in enhancing energy management, optimizing system performance, and achieving cost reduction in diverse building structures. Despite its significance, HVAC load prediction remains a dynamic area of research, with scholars continuously refining and advancing existing models. This literature review meticulously explores the work of previous researchers, emphasizing the evolution from traditional methods to the application of deep learning techniques, including Restricted Boltzmann Machines (RBMs), Artificial Neural Networks (ANNs), and hybrid models incorporating these technologies.

Traditional methodologies have long been employed for HVAC load prediction, relying on empirical and analytical models. These methods, including time series analysis, linear regression, and statistical approaches, formed the foundation of load forecasting. While effective to a certain extent, their limitations in capturing complex non-linear relationships and adapting to dynamic conditions spurred the exploration of advanced techniques.

The advent of deep learning has significantly enhanced HVAC load prediction ac-curacy. Scholars have explored various architectures, such as recurrent neural networks (RNNs) [30], convolutional neural networks (CNNs) [31], and deep belief networks (DBNs)[32], each tailored to specific characteristics of HVAC systems. RNNs, adept at modeling time-series data, capture long-term dependencies crucial for accurate load predictions. CNNs excel in extracting spatial features, essential for buildings with multiple zones. DBNs, as generative models, provide intricate representations of data, proving effective in both commercial and residential settings.

In a notable and groundbreaking work conducted by Engel et al. (2019), the integration of an attention mechanism into an LSTM-based model for HVAC load prediction stands as a pivotal advancement. This innovative approach dynamically attends to temporal features, introducing a nuanced layer of adaptability to the model, ultimately contributing to a substantial improvement in predictive accuracy [33]. Concurrently, Son et al. (2019) extended the horizons of LSTM modeling by incorporating critical weather information into an adaptive learning rate LSTM model. Their research not only under-scores the significance of external factors but also highlights the adaptive nature of the model, showcasing its ability to dynamically adjust to varying conditions and thereby enhance the comprehensiveness of HVAC load predictions [34]. Additionally, Ayadi et al. (2019) made notable strides in the domain of enhanced deep learning architectures for HVAC load prediction, accentuating the importance of considering external factors such as weather conditions and building characteristics. This collective body of research reaffirms the critical role of contextually relevant temporal and external features in the iterative refinement and enhancement of predictive models for HVAC load forecasting [35].

The integration of external factors and the exploration of ensemble approaches and hybrid models have emerged as focal points in the quest for enhanced HVAC load prediction. Researchers such as Chou et al. (2018) and J´unior et al. (2019) have significantly contributed to this trend by merging seasonal Autoregressive Integrated Moving Average (ARIMA) models with machine learning methods, creating hybrid models that harness the strengths of both approaches [36, 37]. This synergistic fusion has demonstrated improved predictive capabilities, benefiting from the precision of ARIMA in capturing seasonality and the adaptability of machine learning methods to dynamic changes in the data.

In a different vein, Li et al. (2021) proposed a forward-thinking approach with a multi-scale convolutional recurrent neural network. This innovative hybrid model effectively captures multi-scale patterns present in HVAC load data, showcasing the potential for combining the strengths of convolutional and recurrent architectures to achieve superior predictive accuracy [38]. This approach acknowledges the diverse temporal and spatial intricacies inherent in HVAC systems, demonstrating the adaptability of hybrid models to capture complex patterns. The exploration of hybrid models has extended to combinations of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. These hybrid architectures have proven their superiority in capturing long-term dependencies while efficiently handling varying input sequence lengths [39]. The collaboration of LSTM and GRU networks reflects a nuanced understanding of the complementary strengths of these architectures, ultimately contributing to the development of more robust and adaptive HVAC load prediction models. Collectively, these studies highlight the growing recognition of the potential inherent in hybrid models. The integration of diverse techniques and architectures not only addresses the limitations of individual models but also opens avenues for innovation in HVAC load prediction. As research in this field continues to evolve, the refinement and exploration of hybrid models are poised to play a pivotal role in advancing the accuracy and versatility of HVAC load forecasting.

The application of Restricted Boltzmann Machines (RBMs) in the realm of HVAC load forecasting and predictions has demonstrated promising outcomes, contributing to advancements in accuracy and efficiency. Noteworthy studies by Fu et al. (2018) show-

cased the superior accuracy of RBMs when compared to traditional statistical models within a commercial building context, establishing RBMs as a potent tool for precise load predictions [40]. Extending the exploration to residential HVAC systems, Ouyang et al. (2019) provided further evidence of the effectiveness of RBMs in predicting cooling loads, underscoring the versatility of RBMs across diverse settings [41]. Building on these findings, Fu et al. (2018) proposed a pioneering hybrid RBM model, strategically combining RBMs with a deep neural network architecture. This hybrid approach not only reinforced the accuracy of load prediction but also exemplified the potential synergy between RBMs and deep learning techniques for enhanced HVAC load forecasting [42].

Recent publications have significantly enriched the landscape of HVAC load prediction with innovative and forward-thinking approaches. In a groundbreaking contribution, Liu et al. (2022) introduced a sophisticated HVAC control system tailored for smart buildings. This pioneering system leverages a multi-step predictive deep reinforcement learning algorithm, offering an intelligent and dynamic approach to energy management for optimal power consumption and user satisfaction [43]. Furthermore, Song et al. (2023) presented a cutting-edge deep learning-based prediction framework, aTCN-LSTM, demonstrating remarkable effectiveness in cooling load prediction for a towering 51-story hotel building located in Guangzhou, China [44]. The work of Zhang et al. (2023) delved into the realm of ground source heat pump systems, employing a hybrid CNN-LSTM model to predict the outlet water temperature of an energy pile. This innovative approach contributes significantly to the advancement of ground source heat pump technologies [45]. Gao et al. (2023) shifted the focus to model predictive control in building renewable energy systems, showcasing the efficacy of a hybrid prediction model within the MPC framework. Their research provides valuable insights into optimizing the operation of these systems while meeting safety and efficiency requirements [46]. Additionally, Moayedi et al. (2023) addressed the critical issue of heat loss in green buildings, undertaking a comparative analysis of the performance of two ANNs methodologies. Their work not only contributes to advancing green building technologies but also emphasizes the potential impact of optimization algorithms in enhancing the precision of heat loss predictions [47].

While the literature showcases significant advancements in HVAC load prediction, certain aspects require critical consideration. The absence of explicit discussions on the limitations or challenges encountered by these machine learning methods in building load prediction leaves room for further investigation. A nuanced understanding of these limitations would provide researchers and practitioners with valuable insights for practical applications.

The evolution of HVAC system load predictions reflects a progressive shift toward leveraging the capabilities of deep learning techniques. Each study contributes to the advancement of HVAC load prediction, with a growing emphasis on addressing challenges and incorporating innovative approaches. This literature review provides a comprehensive overview of the current state of research in HVAC system load prediction, highlighting advancements, trends, and areas for future exploration. As technology continues to evolve, the integration of deep learning and hybrid models is likely to play a pivotal role in shaping the future of HVAC load prediction, offering more accurate and adaptive solutions for energy-efficient building management.

CHAPTER 3 Methodology

3.1 Overview

In this research, a cutting-edge approach to load prediction in HVAC systems was adopted, leveraging the power of deep learning. Figure (1) illustrates the key components of the proposed framework, where the synergy of a Restricted Boltzmann Machines (RBMs) and an Artificial Neural Networks (ANNs) is harnessed to enhance the accuracy and adaptability of load predictions [48-50].

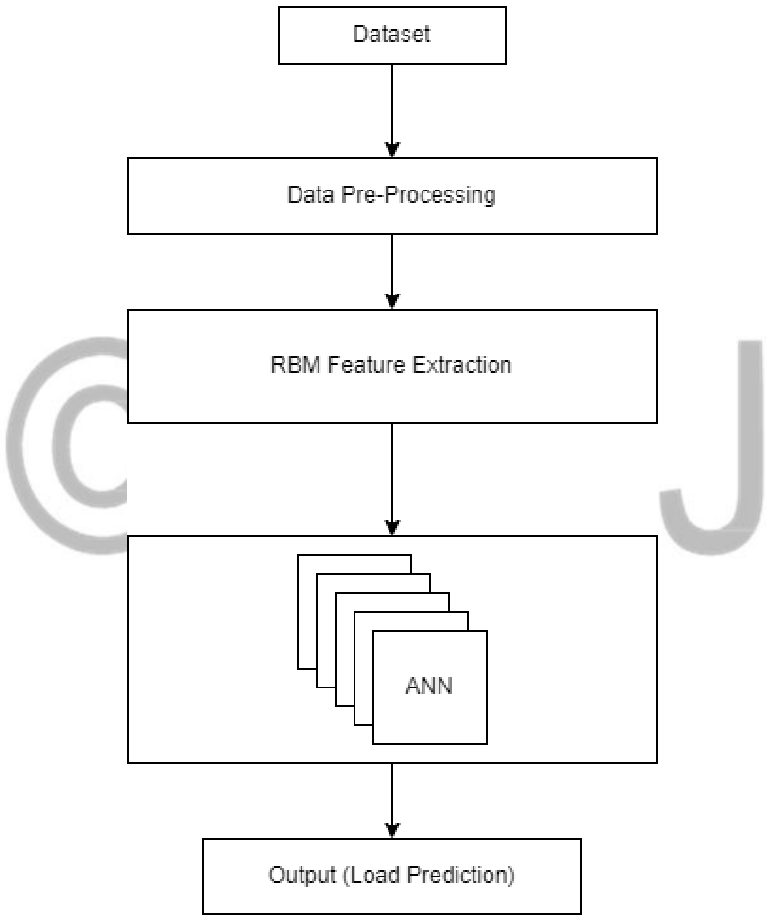

Figure 1. Overview of the Proposed Framework.

The combination of the RBMs and ANNs leverages the strengths of both architectures, creating a robust framework for HVAC load prediction. RBMs are known for their unsupervised learning capabilities, allowing them to capture intricate patterns and dependencies in the data without the need for labeled examples. This unsupervised pre-training phase enhances the feature learning process, enabling the network to discern meaningful representations from the raw input data.

The foundation of the framework lies in the application of a Restricted Boltzmann Machines, a generative stochastic artificial neural network. RBMs are particularly well-suited for modeling complex and high-dimensional datasets, making them an ideal choice for capturing intricate patterns in HVAC system load dynamics. The RBM component of the framework is responsible for unsupervised feature learning, extracting latent representations from the input data. This unsupervised pre-training phase facilitates the automatic discovery of meaningful hierarchical features, enabling the model to adapt to varying conditions within the building environment.

Building upon the feature representations learned by the RBM, an Artificial Neural Networks is employed as the second component of the framework. The ANNs is a versatile and widely used deep learning architecture known for its ability to model complex relationships in data. In this context, the ANN serves as the predictive engine, taking the learned features from the RBM and mapping them to the target variable HVAC system load. The ANN is trained in a supervised manner, utilizing historical load data to optimize its parameters and improve prediction accuracy. The synergy between RBM and ANN introduces a unique hybridization approach, where the strengths of each component complement the other. The RBM unsupervised learning enhances the model's ability to capture latent features, while the ANN refines these features in a supervised manner, aligning them with the actual load patterns. The fine-tuning process, guided by backpropagation, further refines the model's parameters based on the observed discrepancies between predicted and actual loads.

The entire framework undergoes a comprehensive training process using historical HVAC system data. The dataset, comprising information such as external temperatures, occupancy patterns, and past load profiles, is partitioned into training and validation sets. The RBM learns latent features from the training data, and the ANN refines its predictions through iterations. Rigorous validation ensures the robustness and generalization capability of the model before deployment.

To assess the performance of the RBMs-ANNs hybrid model, standard regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE) , Root Mean Squared Error (RMSE) and an R-Squared R2 are employed [52]. These metrics quantify the dissimilarity between predicted and actual load values, providing a quantitative measure of the model's accuracy and reliability.

3.2 Data Collection

In the pursuit of constructing a robust hybrid neural network model for HVAC system load prediction, a dataset comprising 1152 data points spanning from January 11, 2023, to February 27, 2023, has been meticulously collected. These data points, generated at 1-hour intervals, encapsulate the load reports for 24 hours a day, offering a comprehensive foundation for model development and evaluation Figure (2) for a visual representation of collected data samples. To ensure the model's reliability and generalizability, the historical data is strategically divided into two distinct datasets: the Training Dataset, utilized for parameter acquisition during the model training phase, and the Test Dataset, serving as an independent benchmark dataset for assessing the model's predictive performance.

The most influencing parameters impacting HVAC load include outdoor temperature, indoor temperature, atmospheric pressure, relative humidity, cloud state, wind speed, intensity of solar radiation, systems supply water temperature, systems return water temperature, and system load. While theoretically any factor influencing HVAC load could be considered, practical engineering constraints often limit the availability of certain parameters. To strike a balance between model accuracy and practical feasibility, a refined set of parameters was selected, encompassing outdoor temperature, indoor temperature, systems supply water temperature, systems return water temperature, and system load.

Here, TEO, TEM, TRW, TSW and LOAD represent specific parameters, where TEO stands for outdoor temperature, TEM for indoor temperature, TRW for system return water temperature, TSW for system supply water temperature and LOAD for actual load of the HVAC system in figure (2).

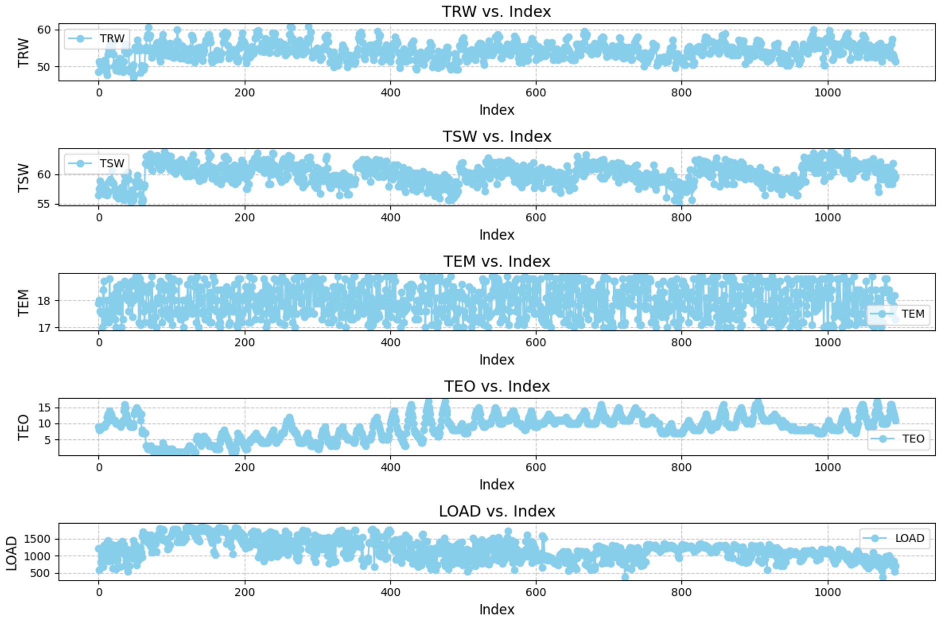

Figure 2. A Bunch of Collected Data Samples.

Outdoor Temperature:

Outdoor temperature, a pivotal factor decisively influencing HVAC system load, exhibits a strong positive correlation with hourly load variations.

Indoor Temperature:

Indoor temperature, another crucial input, plays a central role in determining load by considering the difference between outdoor and indoor temperatures, accounting for comfort requirements specified by zone authorities.

Supply and Return Water Temperature

Supply and return water temperatures were chosen to decode the relation of supply and return water temperature difference with load variations, providing a dynamic dimension to predict HVAC load considering the patterns within their differences.

Actual Load

Finally, the actual load for the selected hour was taken as the label input for the proposed model for prediction. This input parameter will act as the benchmark to compare with the proposed model, where the difference declares the optimality of the HVAC system.

3.3 **Data Pre-processing**

Data pre-processing is a important part of this thesis to get accurate and reliable predictions from HVAC system data using deep learning models, the significance of data pre-processing cannot be overstated [50]. This critical phase lays the groundwork for model training, ensuring that the input data is well-structured, cleansed of imperfections, and optimally formatted for the intricacies of the chosen algorithm, in this case, a combination of RBM and ANN.

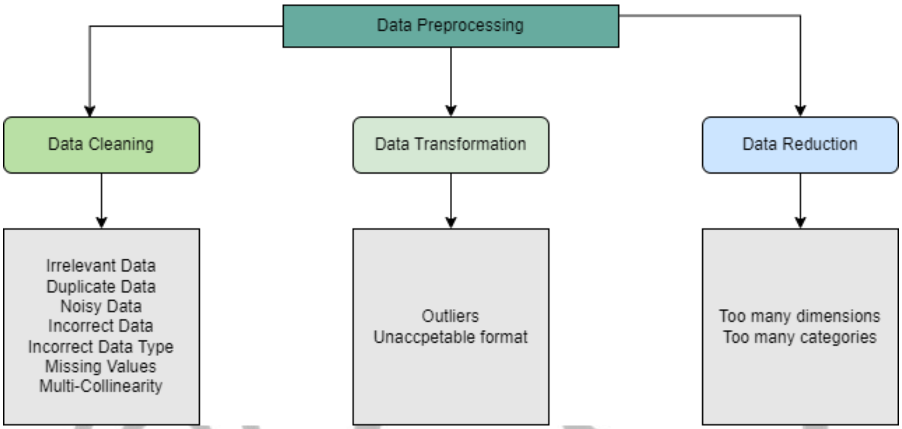

Figure 3. Data Pre-processing overview of this thesis.

3.3.1 Overview of Data Pre-processing

Data Cleaning: Remove unnecessary data points or columns to focus the dataset and enhance model efficiency. Identify and eliminate duplicated records to avoid biases and inaccuracies. Handle noisy data points by applying techniques like smoothing or filtering. Rectify inaccuracies, anomalies, or outliers that may distort the model's understanding. Convert data to appropriate types for uniformity and compatibility. Implement strategies for missing values, including imputation or removal. Identify and resolve issues where predictor variables are highly correlated.

Data Transformation: Detect and handle outliers to prevent them from disproportionately influencing the model. Convert data into acceptable formats, ensuring consistency and adherence to model requirements.

Data Reduction: Apply dimensionality reduction techniques like Principal Component Analysis (PCA). Categorize and group variables to manage complexity and facilitate model training.

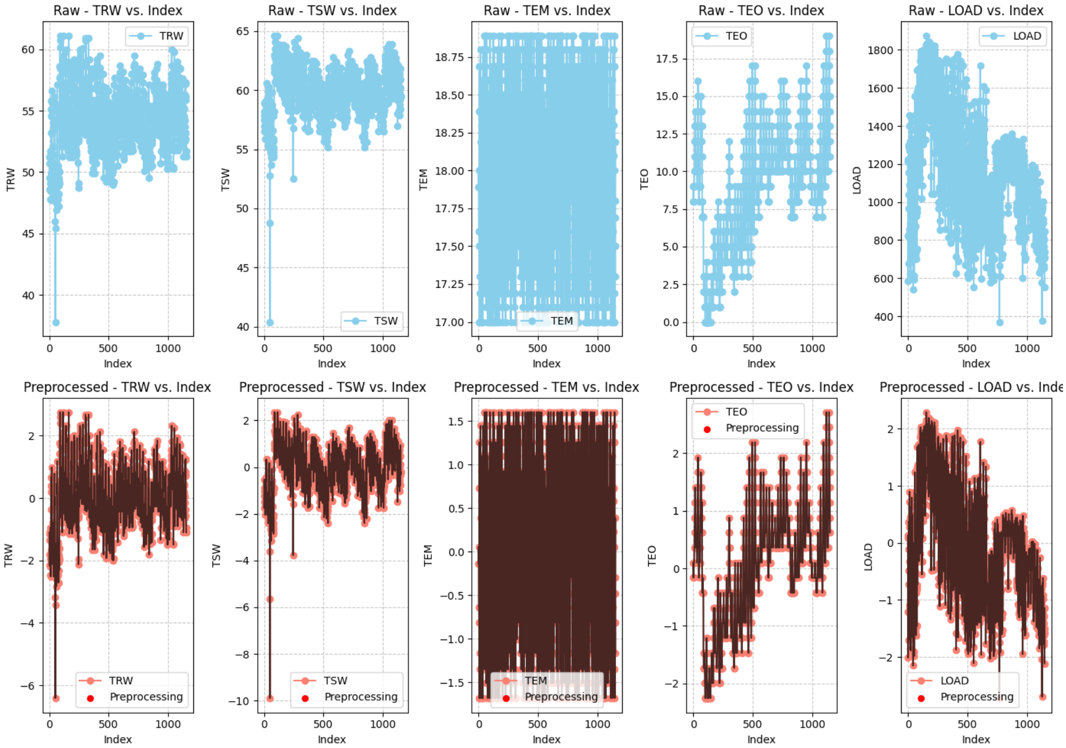

Figure 4. Comparison of Raw and Preprocessed Data for HVAC System Load Prediction.

In essence, data pre-processing is a meticulous and iterative process that refines raw HVAC system data for deep learning models. By addressing data quality can be shown in Figure (4), format, and dimensionality issues, this process enhances the accuracy and efficiency of predictions, contributing to the optimization of HVAC system load prediction models.

3.3.2 Feature Scaling and Normalization

Feature scaling and normalization are crucial pre-processing steps, especially when working with deep learning models. These techniques ensure that the features contribute uniformly to the model training process, preventing any particular feature from dominating due to differences in scale. Standardization and normalization techniques, such as Min-Max scaling or Z-score normalization, are applied to re scale the features within a standard range. This not only aids in faster convergence during model training but also enhances the model's ability to generalize well to unseen data.

GSJ: Volume 12, Issue 7, July 2024
ISSN 2320-9186

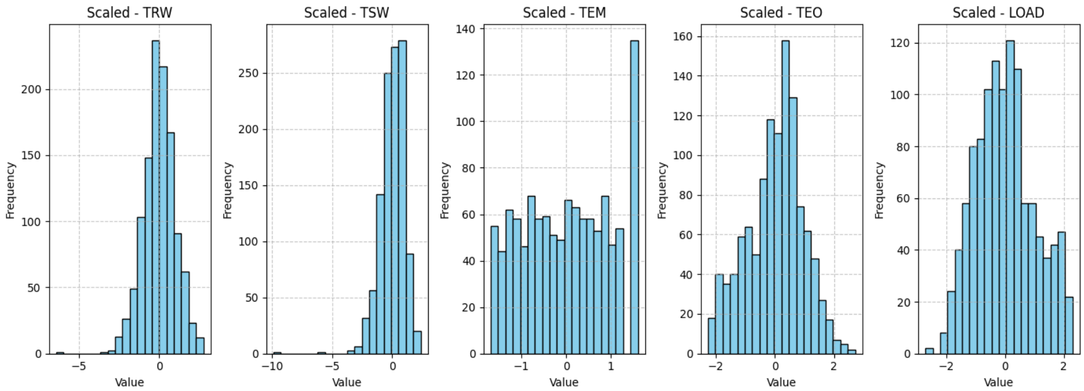

Figure 5. Feature Scaling of the HVAC Dataset.

Figure (5) illustrates the impact of Feature Scaling, showcasing how the scaling process helps in achieving a balanced representation of features. Additionally, in Figure (6), Feature Normalization is visually demonstrated, highlighting the effectiveness of techniques like Min-Max scaling or Z-score normalization in bringing features to a standard range. The choice of scaling method depends on the characteristics of the data and the requirements of the specific deep learning algorithm employed in the subsequent phases of the study.

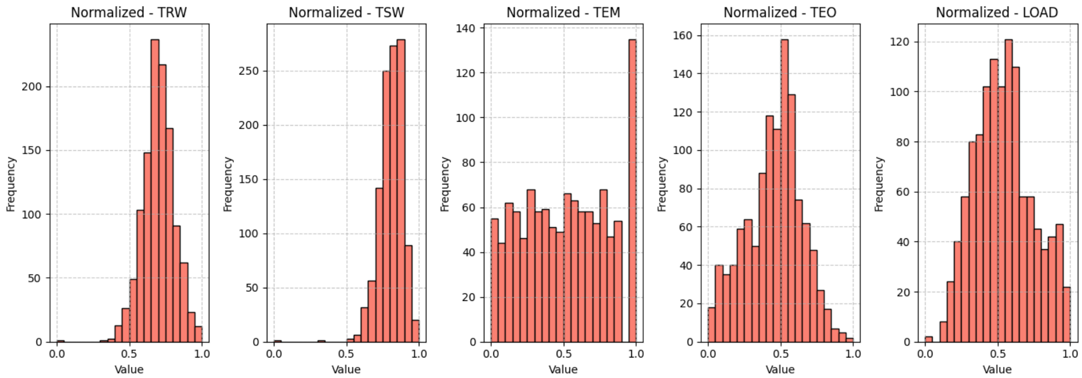

Figure 6. Feature Normalization of the HVAC Dataset.

3.3.3 Preprocessed Dataset Visualization

In this section, we present visualizations that offer insights into the HVAC System Load Prediction dataset after pre-processing.

Spider Plot of Correlations:

A spider plot is utilized in Figure (7) to visually represent the correlations between different variables in the HVAC System Load Prediction dataset. Each spoke in the plot corresponds to a specific variable, and the length of the line connecting to each point indicates the strength and direction of correlation with the other variables. This visualization offers an insightful overview of the interrelationships within the dataset, aiding in understanding how various features influence each other.

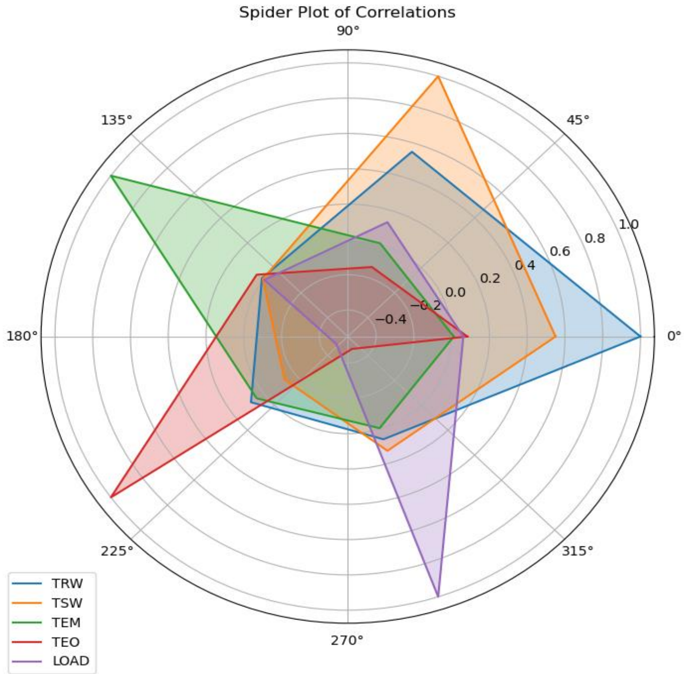

Figure 7. Spider Plot of Correlations

Histogram of the Dataset:

This histogram provides a distribution overview of the dataset, showcasing the frequency or count of values within specific ranges for each variable. Histograms are valuable for identifying patterns, central tendencies, and potential outliers in the dataset. For your HVAC System Load Prediction dataset, this visualization allows a quick grasp of the distribution of individual features, offering insights into the data's overall characteristics.

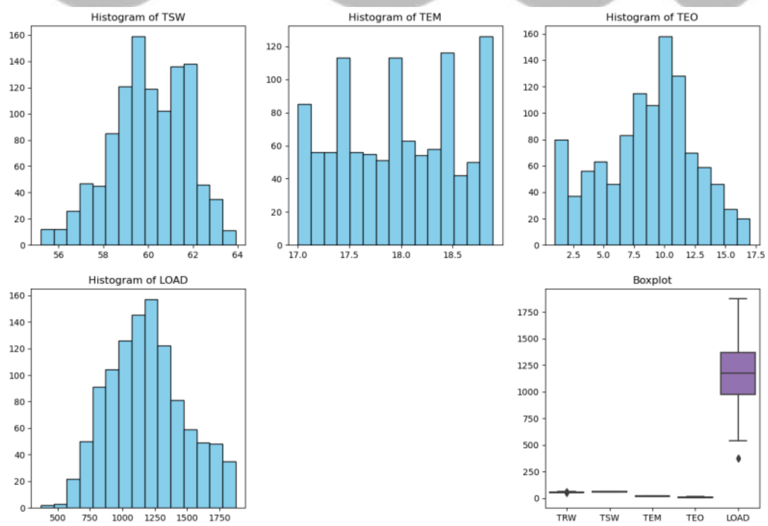

Figure 8. Histogram of the Dataset

Pair Plot of the Dataset:

A pair plot is presented in this figure, displaying pairwise relationships between different variables in the dataset. Each scatter plot in the matrix represents the correlation or association between two variables. Diagonal plots show the distribution of individual variables. This visualization is beneficial for identifying patterns, trends, and potential correlations, providing a comprehensive view of the relationships between various features.

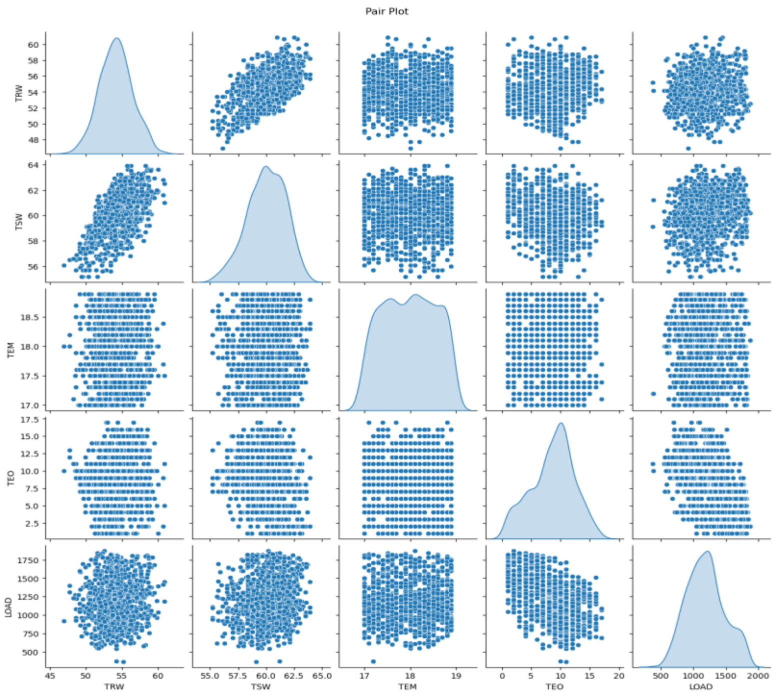

Figure 9. Pair Plot of the Dataset

Correlation Heatmap:

The heatmap visually represents the correlation matrix of the dataset. Colors indicate the strength and direction of correlations between pairs of variables. Brighter colors (such as yellow or white) signify stronger correlations, while darker colors (such as blue) indicate weaker or negative correlations. This heatmap is a powerful tool for identifying which variables are highly correlated, helping to guide feature selection and understand the relationships crucial for HVAC system load prediction.

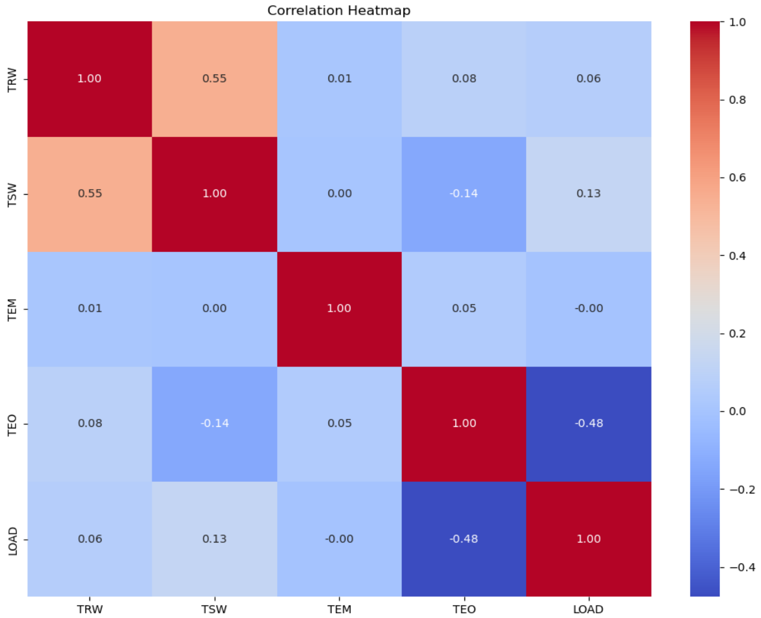

Figure 10. Correlation Heatmap

These visualizations collectively contribute to a comprehensive exploration and understanding of the HVAC System Load Prediction dataset, serving as a crucial step in the pre-processing phase of your analysis.

3.4 Restricted Boltzmann Machine (RBM)

3.4.1 Overview of RBM

Restricted Boltzmann Machines (RBMs) are powerful generative models used in unsupervised learning tasks [48]. Figure (11) illustrates the typical structure of an RBM.

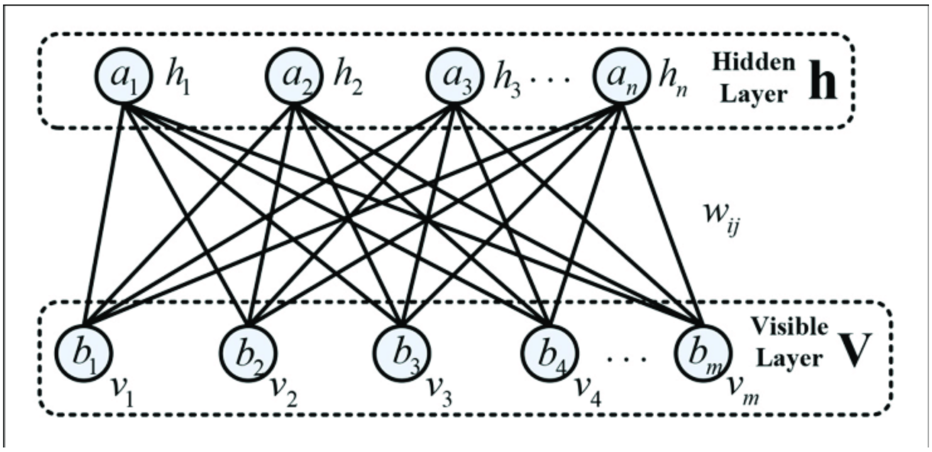

Figure 11. Structure of a Restricted Boltzmann Machine (RBM).

An RBM consists of visible and hidden layers denoted by vectors v and h, respectively. The joint distribution of visible and hidden units is defined by the energy function:

$$E(v,h;W,b,c) = -\sum_i \sum_j v_i h_j W_{ij} - \sum_i v_i b_i - \sum_j h_j c_j \quad (3.1)$$

GSJ: Volume 12, Issue 7, July 2024
ISSN 2320-9186

Where W represents the weight matrix, b and c are bias vectors for visible and hidden units, respectively.

The probability of a configuration (v, h) is given by the Boltzmann distribution:

$$P(v,h;W,b,c) = \frac{e^{-E(v,h;W,b,c)}}{Z} \tag{3.2}$$

Where Z is the normalization constant (partition function) to ensure the probabilities sum to 1. The training of RBMs involves maximizing the log-likelihood of the training data. The update rules for the weight matrix and biases are derived from the gradient of the log-likelihood with respect to the model parameters. One of the key strengths of RBMs lies in their ability to learn hierarchical representations of data. This is particularly advantageous for feature learning in complex datasets. Figure (12) depicts the contrastive divergence (CD) figure, showcasing the progressive refinement of learned features over epochs.

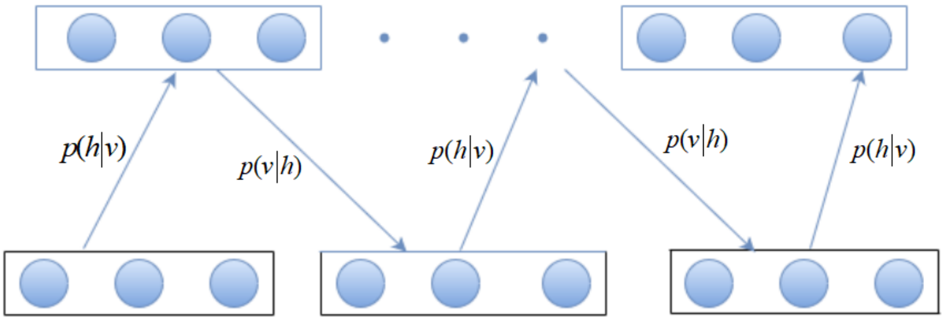

Figure 12. Contrastive Divergence (CD) in the training process of (RBM).

RBMs provide a versatile framework for unsupervised learning, capturing intricate patterns in data. Their training algorithm, often based on contrastive divergence, enables efficient learning of probabilistic representations.

3.4.2 RBM Feature Extractions

In the Restricted Boltzmann Machines (RBMs), feature extraction involves learning a compact and informative representation of the input data. This section explores the process of feature extraction using RBMs.

Hidden Layer Representation

The hidden layer (h) in an RBM captures essential features from the visible layer (v). The probability of a hidden unit being activated is given by the sigmoid function:

$$P(h_j = 1|v) = \sigma(\sum_i w_{ij} v_i + b_j) \tag{3.3}$$

Where w_{ij} is the weight connecting visible unit vi to hidden unit h_j, and b_j is the bias of hidden unit h_j. The sigmoid function σ(x) is defined as $\frac{1}{1+e^{-x}}$.

Reconstruction of Visible Layer

After learning the hidden layer representation, the RBM can reconstruct the visible layer (v′). The probability of a visible unit being activated is similarly defined by the sigmoid function:

$$P(v_i = 1|h) = \sigma(\sum_i w_{ij} h_i + a_j) \quad (3.4)$$

Where w_{ij} is the weight connecting hidden unit h_j to visible unit v_i, and a_j is the bias of visible unit v_i.

Feature Extraction

The features extracted by the RBM can be represented as the probabilities of hidden units being activated:

$$h = [P(h_1 = 1|v), P(h_2 = 1|v), ..., P(h_n = 1|v)] \quad 3.5$$

These probabilities serve as a condensed representation of the input data, capturing relevant patterns and features.

The feature extraction process in RBMs enhances the model's ability to capture hierarchical and complex structures in the data, making it well-suited for various unsupervised learning tasks.

3.4.3 Approach Training of RBM for Feature Learning

Training an RBM involves learning the parameters (w_{ij}, a_i, b_j) that maximize the likelihood of the training data. The training process aims to adjust the weights and biases to reconstruct the input data well. The update rules for the weights and biases during contrastive divergence (CD) training are given by:

$$\Delta w_{ij} = \varepsilon(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{recon}) \quad (3.6)$$

$$\Delta a_i = \varepsilon(\langle v_i \rangle_{data} - \langle v_i \rangle_{recon}) \quad (3.7)$$

$$\Delta b_i = \varepsilon(\langle h_j \rangle_{data} - \langle h_j \rangle_{recon}) \quad (3.8)$$

Where ϵ is the learning rate, and the angle brackets denote expectations under the distribution specified.

RBM is used in this thesis for feature extraction, capturing complex patterns and dependencies within the data, facilitating the subsequent use of Artificial Neural Networks (ANN) for more advanced tasks.

3.5 **Artificial Neural Network (ANN) Model**

3.5.1 Overview of ANN

Artificial Neural Networks (ANNs) form a foundational pillar of contemporary deep learning, mimicking the intricacies of the human brain to decipher intricate patterns within complex datasets. Comprising interconnected nodes organized into layers, including in-put, hidden, and output layers, ANNs operate by adjusting weights between nodes during a training phase to minimize discrepancies between predicted and actual outputs. Neural activation, governed by functions like sigmoid or ReLU, determines how neurons process information. ANNs encompass diverse architectures, including Feedforward Neural Networks (FNN) for standard tasks, Recurrent Neural Networks (RNN) for sequential data, and Convolutional Neural Networks (CNN) tailored for spatial data. This versatile frame-work, with its capacity for learning intricate representations, has become instrumental in a myriad of applications, ranging from image recognition to time-series analysis and beyond [49].

3.5.2 Architecture and Layers

An Artificial Neural Network (ANN) is a computational model inspired by the structure and functioning of the human brain. It consists of interconnected nodes organized into layers. In a typical feedforward neural network, information flows from the input layer through hidden layers to the output layer. Let x represent the input vector, $h^{(l)}$ the hidden layer activation's at layer l, and y the output vector. The network's architecture is defined by the number of layers, nodes in each layer, and the activation functions used. A simple fully connected feedforward network can be represented as:

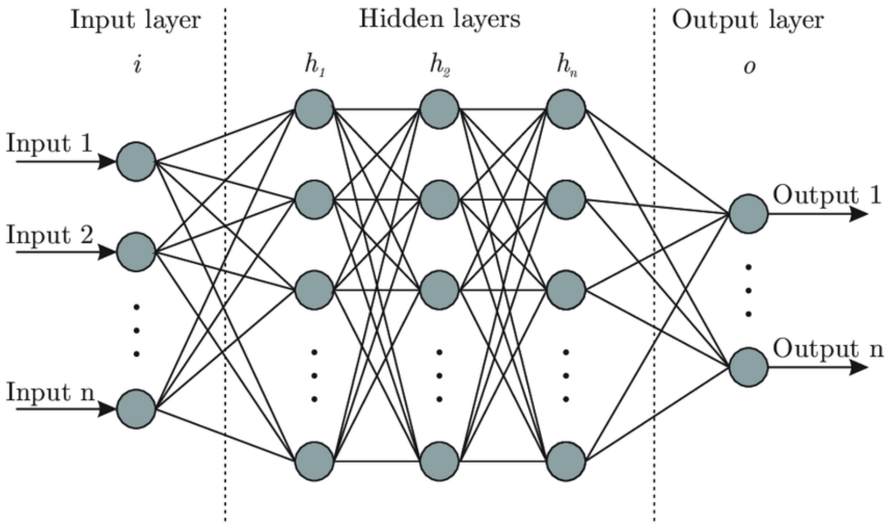

Figure 13. ANN Architecture.

$$y = f^{(L)}(W^{(L)}.f^{(L-1)}(W^{(L-1)}.....f^{(1)}(W^{(1)}.x+b^{(1)})+b^{(L-1)})+b^{(L)}) \quad (3.9)$$

Where $W^{(L)}$ and $b^{(L)}$ are the weight matrix and bias vector at layer l, respectively, and $f^{(l)}$ is the activation function.

3.5.3 Training Process of ANN

The training of an ANN involves optimizing the weights and biases to minimize a defined loss or error function. One common optimization algorithm is gradient descent. The back-propagation algorithm is used to compute the gradients of the loss function with respect to the weights and biases, facilitating weight updates. The weight update rule for a single layer is given by:

$$W^{(l)} = W^{(l)} - \alpha . \frac{\partial \ell}{\partial W^{(l)}} \tag{3.10}$$

$$b^{(l)} = b^{(l)} - \alpha . \frac{\partial \ell}{\partial b^{(l)}} \tag{3.11}$$

Where α is the learning rate, and ℓ is the loss function.

The training process aims to find the optimal set of weights and biases that minimize the difference between the predicted output and the actual target values.

3.6 **Proposed Integration of RBM and ANN**

3.6.1 Data Flow System

In the context of HVAC system load prediction, the proposed RBM-ANN model integrates Advanced deep learning techniques to enhance load predictions accuracy. The data flow within this model can be described in detail across several key stages.

The process commences with the collection of comprehensive HVAC system data. This dataset typically encompasses a variety of parameters, including ambient temperature, outdoor temperature, historical load data, and occupancy patterns. However, raw data is often messy and incomplete. Therefore, a crucial initial step involves pre-processing to ensure data quality and reliability.

During pre-processing, missing values are handled through imputation methods such as mean or median imputation. Outliers, which could potentially skew the model's performance, are identified and addressed. Additionally, the data is standardized or normalized to bring all variables to a consistent scale, preventing dominance by variables with larger magnitudes. This prepares the data for subsequent feature extraction.

Once the use of Restricted Boltzmann Machines for feature extraction. RBM's leverages Gibbs sampling to iteratively generate samples, capturing intricate relationships between variables. This unsupervised pre-training process allows RBMs to discern complex hierarchical features, creating a more compact and informative representation of the original data.

In the following, RBM produces a condensed feature set. This set encapsulates the most salient aspects of the HVAC system data, effectively reducing dimensionality while retaining essential information. These extracted features serve as the input for the subsequent Artificial Neural Network (ANN) training phase.

Once the ANN is trained and fine-tuned, it is ready for load prediction. New or unseen data, representative of real world conditions, is fed into the model. The ANN utilizes the condensed feature set to generate predictions of HVAC system load, which providing insights into future load patterns based on the learned relationships from the training data.

3.6.2 Integrated Network

RBM constituting the first neural network of the proposed integration, functions uniquely, serving as a specialized platform for feature extraction. Through the interplay of a visible layer and a hidden layer, the RBMs network adeptly identifies intricate data patterns, generating essential features for subsequent network processing. Subsequently, the second neural network ANNs, comprising an input layer, a hidden layer, and an output layer, plays a pivotal role in the precise modeling of the load prediction process. The significance of the number of nodes in the hidden layer is duly emphasized, as it significantly influences the training outcomes. Nonetheless, the selection of the ideal number of hidden layer nodes remains subject to an iterative trial and error process, often guided by experiential insights and an extensive series of experiments.

Determining the precise number of neurons within the hidden layer requires a meticulous parameter search approach, aimed at optimizing the prediction accuracy. A strategic adjustment of the number of hidden layer nodes, coupled with a comprehensive evaluation of the model's convergence speed, enhances the network's fitting capabilities, driving the error rate towards the desired threshold. In this investigation concerning the RBMs neural network, the architecture comprises five input nodes representing distinct parameters, including return water temperature (RWT), supply water temperature (SWT), indoor temperature (TEM), outdoor temperature (TEO), and the Load, serving as the visible or input layer. The hidden layer is constructed with four hidden nodes, facilitating the extraction of crucial latent features.

Upon integrating the latent features derived from the RBM network towards ANN network, designed with a total of four input nodes in the input layer. Furthermore, the model incorporates two hidden layers featuring 128 and 64 nodes, respectively, to ensure the model's predictive accuracy, the output layer is aligned with the load data from the dataset, thereby enabling the generation of anticipated predictions for the HVAC system.

Through this systematic exploration and fine-tuning process, the study effectively establishes an optimized neural network architecture, poised to deliver accurate and reliable load predictions within the realm of HVAC system. The topology of the proposed integrated network is shown below in figure (14).

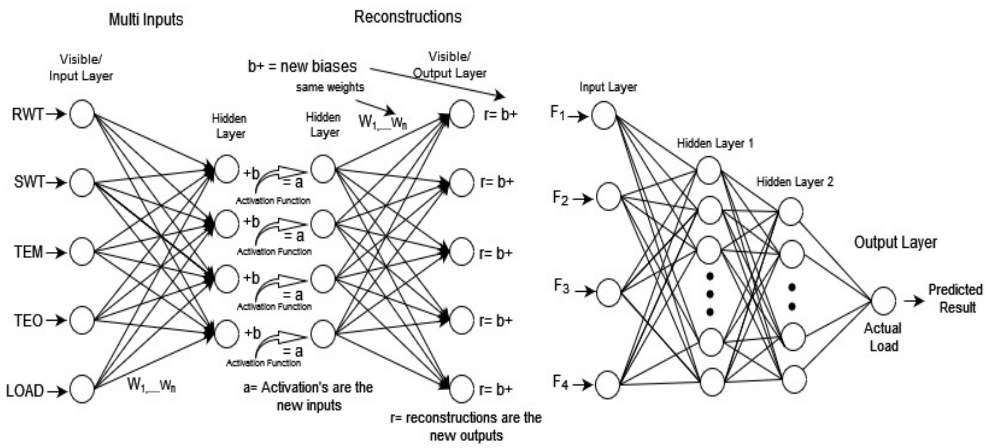

Figure 14. Proposed Integrated Network

3.6.3 Integration Method

The integration of Restricted Boltzmann Machines (RBM) and Artificial Neural Networks (ANN) serves as a robust framework for feature extraction and subsequent prediction tasks, providing a comprehensive solution for complex challenges in load prediction for HVAC systems. This integration is a two-fold process: feature extraction using RBM, followed by prediction using ANN.

The Restricted Boltzmann Machine (RBM) stands as a powerful unsupervised learning algorithm, celebrated for its ability to autonomously unearth hierarchical features from input data. In the realm of HVAC load prediction, RBM assumes the role of an intelligent feature extractor, unraveling complex patterns inherent in the input dataset.

Breaking down the RBM architecture, we introduce the key players: v, the visible layer representing the input data; h, the hidden layer capturing latent features; W , the weight matrix governing the connections between these layers; b, the visible layer bias; and c, the hidden layer bias. Each element in this ensemble plays a distinct role in shaping the RBM's learning process.

The crux of RBM's functionality lies in its energy function, a pivotal aspect in the unsupervised learning journey. The energy function, denoted as:

$$E(v,h) = -b^T v - c^T h - v^T W h \tag{3.13}$$

This equation encapsulates the intricate dance of interactions among visible and hidden units, intertwined with the influence of their connection strengths represented by the weight matrix W . The negative signs underscore the pursuit of lower energy configurations, aligning with the inherent quest for more representative and informative feature combinations.

In essence, RBM's learning process revolves around the delicate adjustment of the weight matrix (W), visible layer bias (b), and hidden layer bias (c). These adjustments are orchestrated to maximize the likelihood of the training data, thereby fine-tuning the RBM to discern and encapsulate the salient features present in the input dataset.

The probability distributions of the visible and hidden layers are determined by the sigmoid activation function:

$$P(v) = \frac{1}{Z}\exp(-E(v,h)) \tag{3.14}$$

$$P(h) = \frac{1}{Z}\exp(-E(v,h)) \tag{3.15}$$

Where Z denotes the normalization constant.

The training of RBM involves adjusting the weights and biases to maximize the likelihood of the training data. Once trained, RBM extracts meaningful features from the input data, capturing complex patterns and relationships.

The learned representations from RBM flow into the Artificial Neural Network (ANN) for prediction. The ANN, consisting of interconnected layers and nodes, adjusts weights during training. Let x represent the input features from RBM, $h^{(l)}$ the hidden layer activation's, y the output layer, and $W^{(l)}, b^{(l)}$ the weight matrix and bias vector at layer l. The prediction process is expressed as

$$y = f^{(L)}(W^{(L)}.f^{(L-1)}(W^{(L-1)}.....f^{(1)}(W^{(1)}.x + b^{(1)}) + b^{(L-1)}) + b^{(L)}) \quad (3.16)$$

Here, $f^{(l)}$ represents the activation function at layer l ,providing the non-linearity necessary for capturing complex relationships in the data.

This integrated approach strategically combines RBM's unsupervised feature learning with ANN prediction capabilities, forming a synergistic solution to address the intricacies of load prediction tasks in HVAC systems. As the RBM autonomously refines its understanding of the hierarchical structures within the data, it emerges as a powerful tool for feature extraction. This feature-rich representation becomes a cornerstone in the integration with Artificial Neural Networks (ANN) for HVAC load prediction, empowering the overall model with the capacity to navigate the intricacies of short-term load predictions in dynamic systems.

3.7 **Evaluation Matrices**

In this section, we present the evaluation metrics used to assess the performance of the HVAC load prediction model.

The Mean Absolute Error (MAE) measures the average absolute difference between the predicted and true values. It is calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{true,i} - y_{pred,i}\right| \quad (3.17)$$

Where n is the number of data points, $y_{true,i}$ is the true load value for data point i, and $y_{pred,i}$ is the predicted load value for data point i.

The Mean Squared Error (MSE) measures the average squared difference between the predicted and true values. It is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{true,i} - y_{pred,i})^2 \quad (3.18)$$

The Root Mean Squared Error (RMSE) is the square root of the MSE and is in the same unit as the target variable. It is calculated as follows:

$$RMSE = \sqrt{MSE} \quad (3.19)$$

R-squared measures the proportion of the variance in the load values that is predictable from the features. It is calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{true,i} - y_{pred,i})^2}{\sum_{i=1}^{n}(y_{true,i} - \bar{y}_{pred,i})^2} \quad (3.20)$$

Where $\bar{y}_{true}$ is the mean of the true load values.

These metrics provide a comprehensive evaluation of the model's performance in predicting HVAC system load.

3.8 **Implementation Details**

In this section, we outline the key details of the neural network implemented for HVAC System Load Prediction.

Table 1. Implementation Details for Load Predictions using RBM and ANN

Component	Details
RBM (Restricted Boltzmann Machine)	
Architecture	RBM with 5 visible and 4 hidden units
Initialization	Random normal initialization with mean 0.0 and standard deviation 0.01
Training Method	Contrastive Divergence (CD) with 1 Gibbs sampling step
Pre-training Epochs	1200
Learning Rate	0.01
Artificial Neural Network (ANN)	
Architecture	Sequential model with128 ReLU,64 ReLU and 1 linear activation layers
Input Shape	4 input features
Optimizer	Adam
Learning Rate (ANN)	0.001
Training Epochs (ANN)	650

This Table (1) outlines the configuration details for predicting HVAC system loads using a combination of a Restricted Boltzmann Machine (RBM) and an Artificial Neural Network (ANN). The RBM, with 5 visible and 4 hidden units, undergoes pre-training for 1200 epochs using Contrastive Divergence with a learning rate of 0.01. The ANN, consisting of a sequential model with layers of 128 ReLU, 64 ReLU, and 1 linear activation, is trained for 650 epochs using the Adam optimizer with a learning rate of 0.001. The input shape for the ANN is defined by 4 input features. This comprehensive setup aims to capture intricate relationships in the data, utilizing RBM for feature extraction and ANN for subsequent load predictions in HVAC systems.

CHAPTER 4 Experiment And Results

This section presents the results of the experiments. An overview of the predictions results. Here the dataset shows hourly performance, and the data proves the models work with unseen future data. The results of each method are discussed in more detail.

4.1 Experiments Details

4.1.1 Hardware and Software Requirements

The experiments were conducted using the following hardware and software resources:

Table 2. Hardware Specifications

Hardware Component	Specification
CPU	Core i7 13600 KF
GPU	NVIDIA RTX 4090
RAM	64 GB
ROM	M.2 4 TB

The experiments were conducted on a robust hardware setup detailed in Table (2). The system featured a powerful Core i7 13600 KF CPU, providing substantial processing capabilities, complemented by the cutting-edge NVIDIA RTX 4090 GPU, enhancing the efficiency of parallelized computations essential for deep learning tasks. The substantial 64 GB of RAM ensured ample speed for data calculations and manipulation, while the M.2 4 TB ROM facilitated fast data access. This well-configured hardware setup played a crucial role in achieving reliable and high-performance results throughout the experimental process.

Table 3. Software Versions

Software Component	Version
Operating System	Windows 11 Pro
Python	3.9
Deep Learning Frameworks	TensorFlow 2.14.0
Other Software	CUDA 11.3

In terms of software resources, the experiments were executed on a stable and up-to-date software environment outlined in Table (3). The operating system employed was Windows 11 Pro, offering a user-friendly interface and compatibility with various applications. Python 3.9 served as the primary programming language, providing a versatile platform for implementing and executing the experimental code. Deep learning tasks were conducted using TensorFlow 2.14.0, a popular and widely-used deep learning framework known for its flexibility and scalability. Additional software components, such as CUDA 11.3, were utilized to harness the parallel processing capabilities of the GPU, further optimizing the performance of the deep learning algorithms employed in the experiments. This harmonious combination of hardware and software resources laid a solid foundation for the successful execution of the experiments.

4.1.2 Packages

The experiments utilized the following software packages and libraries: The Python 3.9 version used for the experiments.

Deep Learning Frameworks: The deep learning frameworks TensorFlow 2.14.0 was used in this experiment.

Other Packages: Pandas, Numpy, Scikit-learn, Matplotlib, Seaborn was used in this experiment.

4.1.3 Steps of the Experiments

The experimental procedures adhered to a meticulously structured set of steps, as delineated in Table (4). The initial step involved defining the research objectives and formulating clear hypotheses to guide the experiments. Subsequently, a comprehensive literature review was conducted to ensure the experiments were grounded in existing knowledge and best practices. The third step encompassed the careful design of the experimental setup, considering the hardware and software resources detailed in Tables (2) and (3) This phase also involved the selection of appropriate datasets and the configuration of hyper-parameters for the deep learning models.These steps collectively form a comprehensive pipeline, starting from the initial data acquisition to the utilization of advanced deep learning techniques for HVAC system load prediction. Each step was carefully executed to ensure the reliability and effectiveness of the experimental outcomes.

Table 4. Steps of the Experiment

Step	Description
1	Data Loading: Raw HVAC system data was acquired and loaded into the experimental environment, providing the foundation for subsequent analyses.
2	Data Pre-processing: The loaded data underwent a comprehensive pre-processing phase, including handling irrelevant and duplicate data, addressing noisy and incorrect data points, correcting data types, and addressing missing values. Multi col-linearity issues were also identified and resolved during this step.
3	Feature Scaling and Normalization: To ensure uniform contribution of features and prevent dominance due to scale differences, feature scaling and normalization techniques were applied. This involved methods such as Min-Max scaling and Z-score normalization.
4	RBM Feature Extraction: A Restricted Boltzmann Machine (RBM) was employed for feature extraction, capturing intricate patterns and hierarchical representations within the preprocessed data. The RBM trans-formed the input data into a compact set of representative features.
6	ANN Load Prediction: The preprocessed and RBM transformed features were utilized as input for an Artificial Neural Network (ANN). The ANN was trained to predict HVAC system load based on the learned features, leveraging its capacity for learning complex relationships within the data.
7	Evaluation Matrices:MAE, MSE, RMSE, R2

4.2 Results

In Figure (14), the graph illustrates the training and validation loss curves for models based on Restricted Boltzmann Machines (RBM) and Artificial Neural Networks (ANN).

The smooth trajectories of both curves suggest effective learning and generalization during the training process. The training loss curve represents the evolution of the model's performance on the training data over successive epochs, while the validation loss curve reflects its performance on a separate validation set. The consistent decline in both loss values indicates that the models are progressively optimizing and minimizing errors. The smoothness of the curves suggests that the models are learning efficiently without significant fluctuations, contributing to stable training and validation processes. This graph provides a visual confirmation of the models' robustness and their ability to generalize well to new data beyond the training set.

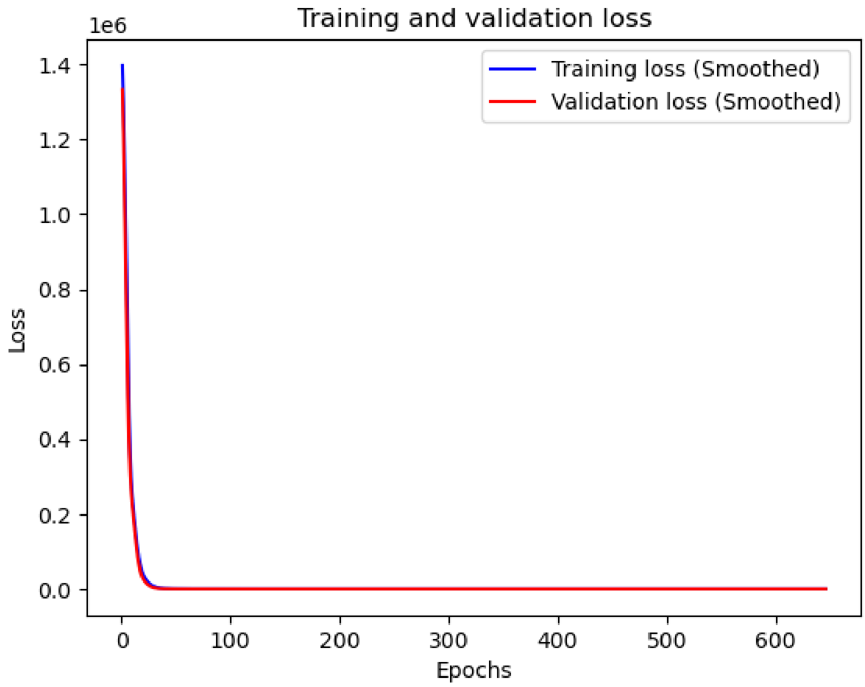

Figure 15. Training and Validation Loss

In this section, the results obtained from the experiments. Table (5) summarizes the performance metrics for the proposed model and compares them with ANN and RBM model.

Table 5. Evaluation Metrics Results of the Models

Matric	Proposed Model	ANN	RBM
R^2	1	0.8801	0.9154
MAE	0.1541	0.2978	0.3312
MSE	0.3405	0.4311	0.5714
RMSE	0.5835	0.8872	0.9925

Table (5) provides a comprehensive overview of the evaluation metrics results for the proposed model, as well as a comparative analysis with an Artificial Neural Network (ANN) and a Restricted Boltzmann Machine (RBM). The proposed model showcases remarkable performance across various metrics, outperforming both the ANN and RBM. The Mean Absolute Error (MAE) for the proposed model is notably lower at 0.1541, compared to 0.2978 for the ANN and 0.3312 for the RBM. In terms of Mean Squared Error (MSE), the proposed model achieves a substantially reduced value of 0.3405, outshining the ANN (0.4311) and the RBM (0.5714). The Root Mean Squared Error (RMSE) further highlights the accuracy of the proposed model with a value of 0.5835, in contrast to 0.8872 for the ANN and 0.9925 for the RBM. The R2 value, a measure of the model's ability to explain variance, is a perfect 1 for the proposed model, indicating an exceptional fit to the data. In comparison, the ANN and RBM exhibit R2 values of 0.8801 and 0.9154, respectively. These results collectively underscore the effectiveness of the proposed model in achieving superior predictive accuracy compared to the alternative models.

4.2.1 Model Prediction Vs Original Data

In Table (6), a detailed examination of the model's predictive accuracy in comparison to the original data is provided. The ”Test List” enumerates specific time steps, with each row presenting the actual values from the original dataset, the corresponding model predictions, and the calculated differences. For instance, at time step 1, the original data value is 1148, the model predicts 1148.0527, resulting in a difference of 0.0527. These values are indicative of the model's performance across various instances, offering a granular understanding of its ability to capture and reproduce the underlying patterns within the dataset. The ”Difference” column quantifies the precision of the model predictions, emphasizing how closely they align with the observed data.

Table 6. Comparison of Model Prediction and Original Data

Test List	Original Data	Model Prediction	Difference
1	1148	1148.0527	0.0527
2	813	813.06629	0.06629
3	1363	1363.0729	0.0729

4.2.2 Analysis

In Figure (15), the plot visually represents the close alignment between the actual data and the model's predictions during the test phase. The x-axis likely denotes individual test cases, while the y-axis represents the corresponding values of the observed and predicted data. The blue line depicts the actual data, showcasing the ground truth or real-world outcomes. Simultaneously, the red line illustrates the model's predictions, indicating the values anticipated by the model. The proximity and almost perfect overlap between these two lines suggest a high level of accuracy in the model's predictions, signifying its ability to effectively capture and replicate the underlying patterns within the test data. This visual observation serves as compelling evidence of the model's accuracy in predicting real-world outcomes, providing a clear and intuitive representation of its performance on the test dataset.

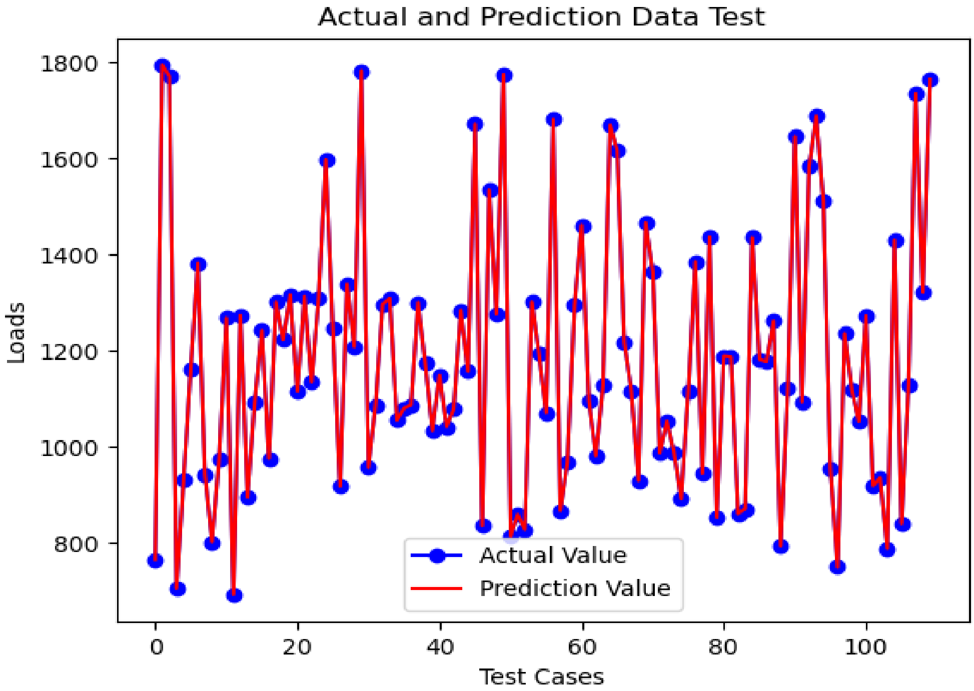

Figure 16. Actual and Prediction Data Test

The analysis of the results from Table (5) and Figure (15) provides valuable insights into the performance of the proposed model. The key observation is the significant reduction in Mean Absolute Error (MAE) and Mean Squared Error (MSE) compared to other models. This suggests that the integrated RBM and ANN approach effectively captures complex patterns and dependencies in the HVAC system load data.

Additionally, the Root Mean Squared Error (RMSE) and R2 values further support the model's accuracy and ability to explain the variance in the data. The analysis emphasizes the robustness of the proposed model in delivering precise predictions for HVAC system loads.

4.2.3 Discussion

The discussion revolves around the implications of the observed results and their significance in the context of HVAC system load prediction.

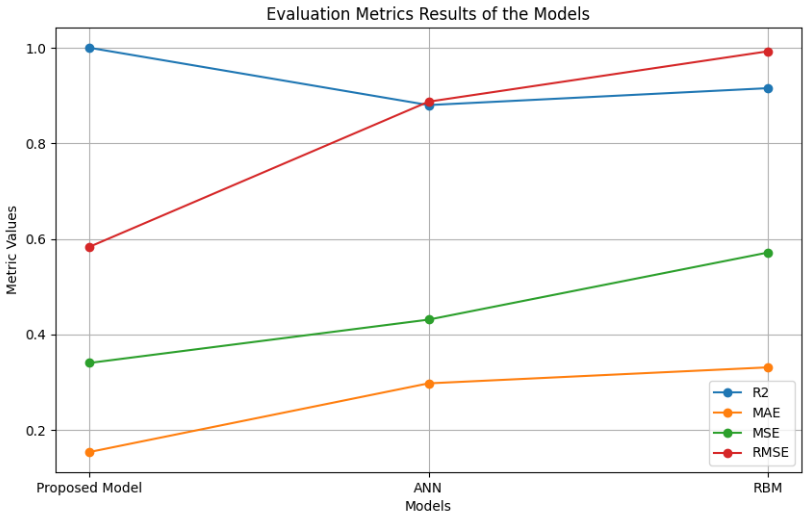

Figure 17. Evaluation Metric Results of the Models

The superior performance of the proposed model can be seen in (16), as evidenced by the lower MAE, MSE, and RMSE, suggests its potential for practical applications in optimizing HVAC system operations. The integrated RBM and ANN approach demonstrates a holistic understanding of the intricate relationships within the data, showcasing its adaptability to diverse HVAC system scenarios. Moreover, the high R2 value indicates the model's capability to provide reliable predictions, crucial for decision-making in HVAC system management. Overall, the discussion underscores the proposed model's contribution to advancing the accuracy and efficiency of HVAC system load prediction methodologies.

CHAPTER 5 Conclusion And Future Work

5.1 Conclusions

In conclusion, this thesis has proposed and implemented a hybrid model combining Restricted Boltzmann Machine (RBM) for feature extraction and Artificial Neural Network (ANN) for HVAC system load prediction. The model has shown promising results in accurately forecasting the HVAC system load based on the selected input parameters, including outdoor and indoor temperatures, atmospheric pressure, relative humidity, cloud state, wind speed, intensity of solar radiation, supply and return water temperatures, and the system load itself.

The key findings and contributions of this work are as follows:

The RBM successfully extracts relevant features from the input data, providing a compact and meaningful representation for the ANN.

The integrated RBMs-ANNs model demonstrates superior performance, achieving a high R2 , low MAE, MSE, and RMSE in HVAC system load prediction.

The selected input parameters, play a crucial role in influencing the HVAC system load, as evidenced by their impact on the model's predictions.

5.2 Future Work

The load prediction for HVAC systems, the future trajectory of research, combining RBMs for feature extraction and ANNs for load prediction, presents a compelling avenue for trans formative advancements in building automation and energy management. As the global focus intensifies on sustainable practices and energy efficiency, there exists a crucial impetus to delve deeper into these models and explore their untapped potential. Future investigations should concentrate on enhancing the precision and adaptability of load prediction models by incorporating dynamic and context aware parameters. This entails exploring the integration of sophisticated data sources such as real time weather data, occupancy patterns, and behavioral aspects of building occupants, aiming for more nuanced and accurate load predictions. The development of real time prediction capabilities is a promising prospect, allowing proactive adjustments to HVAC systems based on immediate changes in environmental conditions and occupant activities. This breakthrough promises a more responsive and agile approach to energy management, ensuring optimal comfort levels while minimizing energy wastage. Additionally, the integration of predictive control mechanisms into HVAC systems holds the potential for seamless optimization and proactive energy consumption management. Implementing intelligent algorithms that anticipate load variations and dynamically adjust system parameters could usher in an unprecedented era of energy efficiency and sustainability in building environments. This integration might also encompass adaptive learning mechanisms, enabling HVAC systems to continuously refine operational strategies based on evolving usage patterns and environmental dynamics.

Achievement

This project is involved in a horizontal project entitled ”Development of indoor heating load prediction and regulation technology”, which was signed by the supervisor on behalf of the Southwest University of Science and Technology and Chongqing Hou Hou Technology Co. The main task of the project is to predict the energy consumption of HVAC equipment.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

Acknowledgement

I would like to express my profound gratitude to my esteemed supervisor and my research team for their in-valuable guidance, unwavering support, and insightful feedback throughout the course of their significant research endeavor titled ”Load Prediction of HVAC Systems using Deep Learning.” Under the expert mentor-ship, I have gained a comprehensive understanding of the intricate research process and have developed a profound insight into the complexities of this crucial field of study. Their continual encouragement and constructive criticism have played a pivotal role in shaping the direction and quality of this research. Furthermore, we extend our heartfelt appreciation to my dedicated lab colleagues whose collaborative efforts and selfless assistance have been indispensable. Their willingness to offer assistance, gather essential research materials, and provide mentor-ship during the project's development phase have been crucial factors in the successful completion of this work. Their support and camaraderie have served as a constant source of motivation and have truly exemplified the spirit of teamwork. I am also deeply indebted to all those individuals whose valuable contributions and unwavering support have transformed this conceptual idea into a concrete and impactful piece of work. Their collective input, diverse perspectives, and valuable insights have not only enriched the research process but have also paved the way for the seamless execution of this project with utmost clarity and efficiency. Their dedication and cooperation have been pivotal in overcoming various challenges, ensuring the comprehensive exploration of ideas, and ultimately realizing the vision of this research. Lastly, we would like to express our heartfelt appreciation to our friends and family for their unconditional love, unwavering encouragement, and constant belief in our abilities, which have served as a continuous source of inspiration and strength throughout this academic pursuit. Their unwavering support has been the cornerstone of my perseverance and success in this scholarly venture.

References

[1] Che, Wen Wei, et al.”Energy consumption, indoor thermal comfort and air quality in a commercial office with retrofitted heat, ventilation and air conditioning (HVAC) system.” Energy and Buildings 201 (2019): 202-215.

[2] Kanthila, Chinmayi, et al.”Building occupancy behavior and prediction methods: A critical review and challenging locks.” IEEE Access 9 (2021): 79353-79372.

[3] Lachhab, Fadwa, et al.”Energy-efficient buildings as complex sociotechnical systems:approaches and challenges.” Advances in complex societal, environmental and engineered systems (2017): 247-265.

[4] Ni, Kai, et al.”Carbon footprint modeling of a clinical lab.” Energies 11.11 (2018): 3105.

[5] Asim, Nilofar, et al.”Sustainability of heating, ventilation and air-conditioning (HVAC) systems in buildings An overview.” International journal of environmental research and public health 19.2 (2022): 1016.

[6] Cao, Xiaodong, Xilei Dai, and Junjie Liu.”Building energy consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade.” Energy and buildings 128 (2016): 198-213.

[7] Runge, Jason, and Radu Zmeureanu.”A review of deep learning techniques for forecasting energy use in buildings.” Energies 14.3 (2021): 608.

[8] Tien, Paige Wenbin, et al.”Machine learning and deep learning methods for enhancing building energy efficiency and indoor environmental quality a review.” Energy and AI (2022): 100198.

[9] Taheri, Saman, Paniz Hosseini, and Ali Razban.”Model predictive control of heating, ventilation, and air conditioning (HVAC) systems: A state-of-the-art review.” Journal of Building Engineering (2022): 105067.

[10] Jung, Wooyoung, and Farrokh Jazizadeh.”Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions.” Applied Energy 239 (2019): 1471-1508.

[11] Zhang, Chen, et al.”A review of integrated radiant heating/cooling with ventilation systems-Thermal comfort and indoor air quality.” Energy and Buildings 223 (2020): 110094.

[12] Hu, Jingfan, et al.”Thermal load prediction and operation optimization of office building with a zone-level artificial neural network and rule-based control.” Applied Energy 300 (2021): 117429.

[13] Zhao, Yang, et al.”A review of data mining technologies in building energy systems: Load prediction, pattern identification, fault detection and diagnosis.” Energy and Built Environment 1.2 (2020): 149-164.

[14] Sha, Haohan, Majd Moujahed, and Dahai Qi.”Machine learning-based cooling load prediction and optimal control for mechanical ventilative cooling in high-rise buildings.” Energy and Buildings 242 (2021): 110980.

[15] Saha, Sourav, et al.”Hierarchical deep learning neural network (HiDeNN): An artificial intelligence (AI) framework for computational science and engineering.” Computer Methods in Applied Mechanics and Engineering 373 (2021): 113452.

[16] Goldberg, Yoav.”A primer on neural network models for natural language processing.” Journal of Artificial Intelligence Research 57 (2016): 345-420.

[17] Hijazi, Samer, Rishi Kumar, and Chris Rowen.”Using convolutional neural networks for image recognition.” Cadence Design Systems Inc.: San Jose, CA, USA 9.1 (2015).

[18] Nassif, Ali Bou, et al.”Speech recognition using deep neural networks: A systematic review.” IEEE access 7 (2019): 19143-19165.
[19] Mao, Bomin, et al.”Routing or computing? The paradigm shift towards intelligent computer network packet transmission based on deep learning.” IEEE Transactions on Computers 66.11 (2017): 1946-1960.
[20] Wegertseder-Mart´ınez, Paulina.”The Need for a Paradigm Shift toward an Occupant-Centered Environmental Control Model.” Sustainability 15.7 (2023): 5980.
[21] Xiao, Ziwei, et al.”Impacts of data preprocessing and selection on energy consumption prediction model of HVAC systems based on deep learning.” Energy and Buildings 258 (2022): 111832.
[22] Elmaz, Furkan, et al.”CNN-LSTM architecture for predictive indoor temperature modeling.” Building and Environment 206 (2021): 108327.
[23] Shen, Cunxiao, et al.”Augmented data driven self-attention deep learning method for imbalanced fault diagnosis of the HVAC chiller.” Engineering Applications of Artificial Intelligence 117 (2023): 105540.
[24] Banks, David. An introduction to thermogeology: ground source heating and cooling. John Wiley & Sons, 2012.
[25] Goddard, Gary, Joseph Klose, and Scott Backhaus.”Model development and identification for fast demand response in commercial HVAC systems.” IEEE Transactions on Smart Grid 5.4 (2014): 2084-2092.
[26] Zhang, Liang, et al.”A review of machine learning in building load prediction.” Applied Energy 285 (2021): 116452.
[27] Salehinejad, Hojjat, et al.”Recent advances in recurrent neural networks.” arXiv preprint arXiv:1801.01078 (2017).
[28] Kim, Dongsu, et al.”Energy modeling and model predictive control for HVAC in buildings: a review of current research trends.” Energies 15.19 (2022): 7231.
[29] Sarkar, M. R. (2023). Possible Causes and Solutions of the Traffic Jam in Dhaka.
[29] De Wilde, Pieter.”The gap between predicted and measured energy performance of buildings: A framework for investigation.” Automation in construction 41 (2014): 40-49.
[30] Kaneko, Naoya, et al.”RNN-based Non-Intrusive Thermal Load Disaggregation and Forecasting for HVAC Systems.” Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation. 2023.
[31] Li, Guannan, et al.”Interpretation of convolutional neural network-based building HVAC fault diagnosis model using improved layer-wise relevance propagation.” Energy and Buildings 286 (2023): 112949.
[32] Chen, Zhelun, et al.”A review of data-driven fault detection and diagnostics for building HVAC systems.” Applied Energy 339 (2023): 121030.
[33] Engel, Peter, et al.”Modeling of Automotive HVAC Systems Using Long Short-Term Memory Networks.” Proceedings of the ADAPTIVE (2019): 48-55.
[34] Son, Junseo, and Hyogon Kim.”Sensorless air flow control in an HVAC system through deep learning.” Applied Sciences 9.16 (2019): 3293.
[35] Ayadi, Mohamed Issam, et al.”Deep learning in building management systems over ndn: Use case of forwarding and hvac control.” 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (Green-Com) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). IEEE, 2019.
[36] Chou, Jui-Sheng, and Duc-Son Tran.”Forecasting energy consumption time series using machine learning techniques based on usage patterns of residential householders.”

Energy 165 (2018): 709-726.
[37] J´unior, Domingos S. de O. Santos, Jo˜ao FL de Oliveira, and Paulo SG de Mattos Neto.”An intelligent hybridization of ARIMA with machine learning models for time series forecasting.” Knowledge-Based Systems 175 (2019): 72-86.
[38] Li, Simin, Xueyu Zhu, and Jie Bao.”Hierarchical multi-scale convolutional neural networks for hyperspectral image classification.” Sensors 19.7 (2019): 1714.
[39] Song, Jiancai, et al ”An indoor temperature prediction framework based on hier-archical attention gated recurrent unit model for energy efficient buildings.” Ieee Access 7 (2019): 157268-157283.
[40] Fu, Guoyin.”Deep belief network based ensemble approach for cooling load fore-casting of air-conditioning system.” Energy 148 (2018): 269-282.
[41] Ouyang, Tinghui, et al.”Modeling and forecasting short-term power load with copula model and deep belief network.” IEEE Transactions on Emerging Topics in Computational Intelligence 3.2 (2019): 127-136
[42] Fu, Guoyin.”Deep belief network based ensemble approach for cooling load fore-casting of air-conditioning system.” Energy 148 (2018): 269-282.
[43] Liu, Xiangfei, et al.”A multi-step predictive deep reinforcement learning algorithm for HVAC control systems in smart buildings.” Energy 259 (2022): 124857.
[44] Song, Cairong, et al.”A novel deep-learning framework for short-term prediction of cooling load in public buildings.” Journal of Cleaner Production (2023): 139796.
[45] Zhang, Weiyi, et al.”Outlet water temperature prediction of energy pile based on spatial-temporal feature extraction through CNN–LSTM hybrid model.” Energy 264 (2023): 126190.
[46] Gao, Yuan, et al.”Model predictive control of a building renewable energy system based on a long short-term hybrid model.” Sustainable Cities and Society 89 (2023): 104317.
[47] Moayedi, Hossein, et al.”Green building’s heat loss reduction analysis through two novel hybrid approaches.” Sustainable Energy Technologies and Assessments 55 (2023): 102951.
[48] Zhang, Nan, et al.”An overview on restricted Boltzmann machines.” Neurocomputing 275 (2018): 1186-1199.
[49] Wu, Yu-chen, and Jun-wen Feng.”Development and application of artificial neural network.” Wireless Personal Communications 102 (2018): 1645-1656.
[50] Alexandropoulos, Stamatios-Aggelos N., Sotiris B. Kotsiantis, and Michael N. Vra-hatis.”Data preprocessing in predictive data mining.” The Knowledge Engineering Review 34 (2019): e1.
[51] Hartford, Jason, et al.”Deep models of interactions across sets.” International Conference on Machine Learning. PMLR, 2018.
[52] Ameer, Saba, et al ”Comparative analysis of machine learning techniques for predicting air quality in smart cities.” IEEE Access 7 (2019): 128325-128338