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Research paper

Deep learning-based optimization of energy utilization in IoT-enabled smart cities: A pathway to sustainable development

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ABSTRACT

As metropolitan populations increase and the demand for environmentally friendly lifestyles increases, the growth of IoT-enabled smart cities promises a viable route for overcoming the complex concerns of energy management, sustainable development, and financial optimization. By presenting a deep learning method to energy management, this research article delves into the quest of sustainability in smart cities. The study describes an innovative framework for optimizing energy utilization in IoT-connected smart cities by leveraging the potential of deep learning algorithms. It uses real-time data from a number of sources, including sensors, devices, as well as smart grids, to allow smart energy saving and efficiency decisions. The proposed approach conforms to dynamic utilization trends and gives precise demand estimates by utilizing deep learning models including neural networks and recurrent neural networks (RNNs). Through detailed simulations and realistic case studies done in several smart cities throughout the world, the research paper proves the effectiveness of the deep learning-based strategy. The findings show significant reductions in energy usage, cost savings, and significant contributions to greenhouse gas emissions elimination, eventually increasing environmental sustainability. Additionally, the framework's versatility and scalability highlight its application in a variety of urban situations. This study article not only tackles current energy management issues, but it also sets the framework for a more environmentally conscious as well as effective urban future.

1. Introduction

The twenty-first century is experiencing an unparalleled worldwide trend: our planet's growing urbanization. Cities are experiencing major alterations as more people rush to them in pursuit of better living conditions and economic possibilities. The idea of smart cities started to gain traction in response to the issues brought by urbanization. Smart cities use cutting-edge technology to optimize resource utilization, improve quality of life, while lowering environmental impact (Almalki et al., 2023; Khan et al., 2020; Almihat et al., 2022). The use of the Internet of Things (IoT), which integrates a plethora of gadgets, sensors, as well as infrastructure to build intelligent metropolitan environments, is essential to the smart city approach. Energy management is one of the most critical issues in the establishment of smart cities (Li, 2022). These cities' energy demands rise dramatically as they become more technologically advanced. In order to guarantee the long-term viability of smart cities, efficient as well as intelligent energy management systems must be developed. The objective is not only to satisfy the energy requirements of a growing urban population, but to do so in an environmentally friendly manner that minimizes environmental impact and costs. This objective is especially important in the Kingdom of Saudi Arabia, which is rapidly urbanizing and modernizing (Abou-Korin and Al-Shihri, 2015). Fig. 1 depicts an IoT-based sustainable smart city, highlighting the interconnected network of gadgets and technological innovations that contribute to urban sustainability.

Saudi Arabia is undergoing an unprecedented modernisation change, with its cities becoming smarter and more linked. Riyadh, Jeddah, and various other Kingdom cities are adopting IoT technologies to improve several elements of urban life, including as transportation, medical care, security, as well as energy management. Considering the high energy consumption of urban infrastructure, industries, as well as daily life, energy management comes out as a critical component. Conventional energy management systems frequently come inadequate in smart cities, wherein consumption patterns are very dynamic and real-time modifications are required to maintain efficiency. Artificial intelligence (AI) as well as deep learning approaches has emerged as possible solutions in this arena. Deep learning, an aspect of AI, includes neural networks along with additional machine learning algorithms that can analyze

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large datasets, adapt to shifting patterns, and generate reliable forecasts (Doheim et al., 2019; Aljoufie and Tiwari, 2022; Alotaibi and Potoglou, 2018; Anwar and Oakil, 2023).

The paper investigates the vital convergence of sustainability, IoT-enabled smart cities, as well as deep learning-driven energy management. It investigates how deep learning techniques might be used in smart cities to optimise energy usage, save expenses, and improve environmental sustainability. The focus shifts to Saudi Arabian smart cities, where the combination of IoT and deep learning has enormous potential for tackling the Kingdom's unique energy concerns. The goals of this research article are twofold: first, to explain the importance of deep learning in energy management in the setting of smart cities, as well as second, to evaluate the relevance of these approaches within Saudi Arabia's distinctive metropolitan environment. We intend to deliver an in-depth understanding regarding the way deep learning might improve sustainability in the Kingdom of Saudi Arabia's IoT-enabled smart cities through a combination of interdisciplinary research, actual case studies, as well as simulations.

The need to develop an efficient and trustworthy load forecasting system capable of handling the broad array of load data arriving from homes, businesses, as well as industrial data sources is at the top of the list of issues confronting successful energy management (Ahmad and Zhang, 2021; Aslam et al., 2021; Ibrahim et al., 2020). Despite the availability of several load forecasting algorithms, their flexibility and usefulness in the context of IoT-edge computing situations remains relatively studied and under-implemented. The integration of IoT networks and their ability to provide smooth communication between networked devices for energy management mandates the development of creative solutions that can meet the particular needs of such environments. Additionally, the resource-constrained features of IoT edge devices, also known as edge nodes, highlight the requirement for a compact load forecasting strategy that minimises computational difficulty. This optimisation is crucial to ensuring real-time operation, which is required for properly controlling the dynamic energy demands facing smart units prevalent in contemporary smart cities.

To address the aforementioned multiple issues, this research study proposes a novel approach for estimating energy usage in various IoT contexts. This research makes a substantial contribution to the discipline in various respects. First, it introduces a unique deep learning (DL) model for load forecasting, which incorporates Spatial Transformer (ST) sub-modules for capturing hidden spatial patterns and a Temporal Transformer sub-module to describe temporal dependencies within input sequences. These transformer modules enable parallelization while efficiently modelling the data's spatial-temporal features. This work is notable for being the first to investigate transformer layouts in the context of Load/Energy forecasting. Furthermore, the research tackles energy management by implementing a strong IoT architecture that integrates energy providers and consumers into a unified platform. This suggested system is distributed in different areas of smart cities, connecting to a cloud server via IoT networks to ease the exchange of energy demands and warnings of approaching needs. Synchronization with smart grids provides the seamless and efficient transmission of the exact quantity of energy necessary, resulting in an environmentally friendly approach to energy management (Bayram and Ustun, 2017; Fadel et al., 2015). Finally, the study validates the effectiveness of the suggested approach by a comprehensive set of experiments carried out on resource-constrained IoT devices placed in diverse smart city sectors. The outcomes not only support the proposed framework's practicability, but also shed light on its capacity to revolutionize the energy management environment in smart cities.

Policy makers, city planners, as well as energy managers can build improved and environmentally friendly energy policies for today's smart cities as well as future huge metropolitan areas by integrating the findings of this study with creative technical breakthroughs. This research is a practical step towards realising the possibilities of smart, sustainable urban circumstances, where technology functions as an accelerator for a brighter, greener, and increasingly sustainable future.

The subsequent sections of this research study follow an orderly sequence. Section 2 explores into a thorough examination and analysis of the literature, offering perspectives on existing knowledge and establishing the background for the proposed paradigm. Section 3 introduces the proposed framework for improving sustainability in IoT-

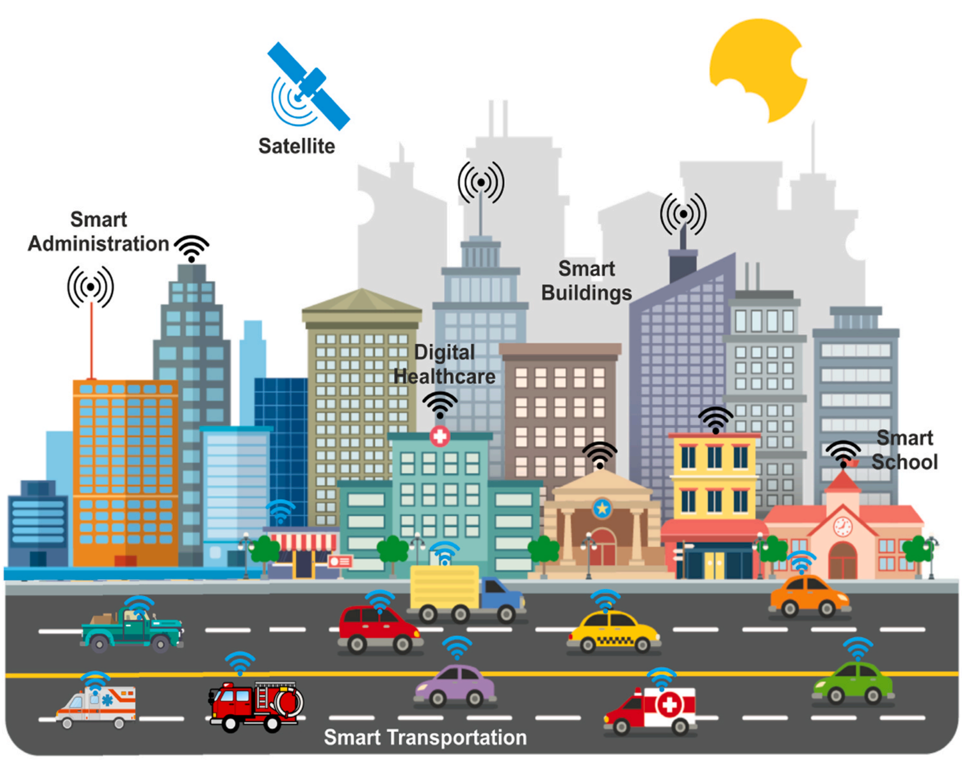

Fig. 1. An illustration of IoT based sustainabile smart city.

enabled smart cities through a deep learning approach to energy management. Section 4 then synthesizes the research findings, providing an assessment of the framework's performance using multiple metrics. Section 5 begins a more in-depth discussion, presenting a nuanced examination of the findings and their consequences. Finally, Section 6 brings the research study to a conclusion with summarizing major findings and outlining future research directions in the field of sustainable energy management in smart urban environments.

2. Related works

The literature on smart city energy management demonstrates the growing focus on the incorporation of deep learning models with IoT technology to handle the multiple issues involved with load forecasting as well as energy optimisation. Abdel-Basset et al (Abdel-Basset et al., 2021). present the Energy-Net stack, a deep learning model designed for forecasting short-term energy use. This paradigm makes use of spatio-temporal components, which combine temporal transformers (TT) as well as spatial transformers (ST). Particularly, the study demonstrates higher forecasting precision with a low root mean square error (RMSE), demonstrating deep learning's potential in energy prediction. The emphasis, however, is solely on forecasting, with no detailed examination of the larger energy management situation.

Zhang et al (Zhang et al., 2021). strengthen the literature by providing the IoT-SGE framework for smart cities. Their approach emphasises the importance of IoT in providing accurate energy regulation via ubiquitous surveillance and secure transmission. The focus is on efficient energy management made possible by deep reinforcement learning. The study emphasises the potential for cost reductions via accurate energy demand forecasting. It does, however, focus exclusively on the planning as well as assessment of smart power systems without directly addressing the complexities of load forecasting.

Abbas et al (Abbas et al., 2020). use deep extreme learning machines to conduct predictive modelling for integrated cycle power plants. The study looks into the possibilities of deep learning algorithms for data processing, with an emphasis on attaining high reliability and low error rates. In regards to accuracy, their study outperforms prior studies, suggesting a possible avenue for the incorporation of sophisticated methods of machine learning in the energy industry.

Belli et al (Belli et al., 2020). examine essential components of smart city IoT infrastructure, focusing on advances done in Parma, Italy. The research is mainly focused on urban mobility in the setting of smart cities, providing useful insights into IoT technology deployment. The primary focus, however, is on the role of infrastructure rather than predictive modelling or load forecasting.

Awan et al. (2021) present a machine learning technique based on particle swarm optimisation for smart grids, with a focus on collaborative execute-before-after dependency-based needs. The suggested approach outperforms standard optimisation methods, demonstrating its ability to reduce costs, improve peak-to-average ratios, and enhance power variance mean ratios.

Haseeb et al. (2021) describe an intelligent and trustworthy edge-enabled computing (ISEC) strategy for sustainable cities, utilising Green IoT. Deep learning for data routing optimisation is discussed in their investigation, with an emphasis on energy management and data security. The findings from the experiment show improved outcomes across a wide range of measures, giving a comprehensive approach to smart city sustainability.

Ejaz et al. (2017) describe a common framework for energy-efficient optimisation as well as planning of IoT-based devices, providing a complete overview of energy management difficulties in smart cities. The paper explores energy harvesting's prospective role in prolonging device lifetimes and presents case studies on energy-efficient management in smart homes as well as wireless power transmission for IoT gadgets in smart cities.

Employing the Multi-Objective Distributed Dispatching algorithm (MODDA), Xiaoyi et al. (2021) investigate the insertion of IoT into smart electricity grids. The research looks at the tradeoff among utility function cost as well as energy usage, with an emphasis on the role of IoT in efficient green energy management. The algorithm's efficiency in reducing system costs and energy usage is demonstrated by experimental findings. Table 1 summarises related publications on energy management in smart cities, offering a thorough overview of significant findings and trends in the literature.

Although the existing literature offers useful insights into specific elements of energy management as well as IoT integration in smart cities, there is a significant research gap. The present body of work is frequently focused on either load forecasting models or the larger IoT infrastructure, highlighting the need for an integrated strategy that includes both predictive modelling and comprehensive energy

Table 1
Meta-Analysis Table of Related Works on Energy Management in Smart Cities.

Study	Methodology	Key Findings
(Abdel-Basset et al., 2021).	DL model (Energy-Net) with ST and TT submodules	Efficient load forecasting with RMSE of 0.354 on IHPEC data. Spatial-temporal modeling with improved self-attention. Suitable for resource-constrained IoT devices.
(Zhang et al., 2021).	IoT-SGE for smart cities using deep RL	Comprehensive methodology for planning and evaluating smart power systems. IoT-enabled smart energy management system. Effective use of IoT sensors for energy consumption prediction and cost savings.
(Abbas et al., 2020).	Deep Extreme Learning Machine (DELM)	Predictive model for combined cycle power plant output with 98.6 % accuracy. High reliability and minimum error rate. Demonstrates the superior performance of DELM in data sequence analysis.
(Belli et al., 2020).	Analysis of IoT infrastructure in Parma	Analysis of key aspects of IoT infrastructure in smart cities. Focus on innovations in Parma, Italy.
(Awan et al., 2021).	Particle swarm optimization-based ML algorithm	Proposed collaborative execute-before-after dependency-based requirement algorithm for smart grid. Outperforms PSO and inclined block rate in terms of cost reduction, peak to average ratio, and power variance mean ratio.
(Haseeb et al., 2021).	ISEC model with Green IoT	Intelligent and secure edge-enabled computing (ISEC) model for sustainable cities. Improved performance in energy consumption, network throughput, end-to-end delay, route interruption, and network overhead.
(Ejaz et al., 2017).	Unifying framework for energy-efficient optimization	Framework for energy-efficient optimization and scheduling of IoT-based smart cities. Case studies on energy-efficient scheduling in smart homes and wireless power transfer for IoT devices.
(Xiaoyi et al., 2021).	Multi-Objective Distributed Dispatching (MODDA)	Integration of IoT in smart electrical grids using MODDA. Efficient energy management with a tradeoff between cost and consumption. Reduction of substantial energy waste in smart buildings equipped with the proposed IoT system.
Contribution of This Research	Deep Learning for Saudi Arabian Smart Cities	Optimized energy utilization with a focus on adaptability and efficiency across diverse urban scenarios.

management within the wider setting of smart cities. Furthermore, the use of such frameworks in resource-constrained IoT scenarios, especially within the Kingdom of Saudi Arabia, is unexplored.

This study aims to fill a research gap through the development of a novel deep learning-based framework that not only tackles short-term load forecasting obstacles but also seamlessly incorporates into the energy management structures of IoT-enabled smart cities in the Kingdom of Saudi Arabia. For appropriate load predictions, the proposed system integrates spatiotemporal modules with advanced transformer topologies. Furthermore, our research thoroughly investigates the use of this framework in real-world, resource-constrained IoT situations, thereby contributing to the actual implementation of sustainable energy management solutions in smart cities.

3. Materials and methods

This section provides the foundation of empirical investigation by offering a full overview of the research design, data collecting, and analytical processes used to answer the objectives of the study. The rigorous selection and implementation of materials and methodology plays a critical part in the development as well as validation of the proposed framework in this inquiry focused on boosting sustainability in IoT-enabled smart cities using a deep learning approach to energy management. This section provides a complete overview of the research strategy, data gathering and integration from many sources, preprocessing processes performed to refine the dataset, and extensive techniques for feature engineering, model creation, training, and validation. Every phase of the proposed framework is supported by a well-defined set of components and approaches, assuring the scientific rigour required to derive significant insights and promote sustainable practices in urban energy management.

We used a systematic strategy to tailor our deep learning models for different urban settings in order to address the significance of customised model selection based on particular metropolitan features. In order to make sure that our models were both efficient and able to be customised to the particular features of each city, this customisation procedure was crucial. In Smart City A, we incorporated extensive urban data into our model and concentrated on implementing it throughout the entire city. This contained data on energy consumption trends, infrastructure details, and demographics. We modified the model to precisely represent the city's overall energy use by combining these many data sets, making more precise load forecasting as well as energy management possible.

The customisation procedure in Smart City B entailed focussing on a particular city district that was recognised for having distinct patterns of energy usage. We modified our model to take into consideration localised elements including energy distribution networks, peak demand periods, as well as district-specific infrastructure. Our model was able to more successfully optimise energy management within the intended region due to this district-level customisation. We ran a pilot program for Smart City C, which provided a controlled setting for us to test and improve our methodology. We regularly modified the model during this phase in response to comments from the pilot region and real-time data. We were able to adjust the model's parameters through this iterative method, making it capable of adjusting to the unique energy requirements and consumption patterns of the pilot area.

We worked with regional businesses in Smart City D to adapt our industrial energy management model. This required us to incorporate data particular to our business into our model, especially manufacturing cycles and energy-intensive procedures. We improved the model's ability to control and optimise energy use in industrial processes by adjusting our methodology to the particular needs of the industrial sector. Our goal was to show off our deep learning models' versatility and agility. By tailoring the models to the unique features of every urban situation, we made sure that our method could successfully handle the many energy management issues that various cities face. This comprehensive customisation procedure demonstrates the usefulness and possible influence of our study in a range of real-world contexts.

As we embarked on the methodology excursion, our study carefully built a roadmap to navigate the complicated world of energy management in IoT-enabled smart cities. Our approach to gathering data was based on the strategic placement of a variety of IoT devices spread throughout several metropolitan areas. We used a methodical strategy to choose the IoT sensors and figure out where in smart cities they should be placed. First, we determined the main residential, commercial, as well as industrial zones in the city where there are notable differences in the patterns of energy usage. Based on their precision, dependability, as well as compatibility with the current infrastructure, we chose our sensors. We took into account elements like high energy consumption regions, possible data sources for identifying important usage trends, and smart grid integration while determining the best location. To guarantee data quality, we also assessed external factors and possible sources of disturbance. The city's energy environment is accurately represented and extensive coverage is ensured by its strategic placement.

A key element in improving our framework's precision and efficiency was its connection with the current smart grid infrastructure. To facilitate real-time data sharing, we created a smooth connection among the smart grid systems as well as the Internet of Things sensors placed across the city. Through this connection, data on energy use and grid performance measures may be synchronised, giving rise to a comprehensive picture of the city's energy environment. We made sure that the energy consumption estimates and management plans were based on real grid circumstances and demand fluctuations by coordinating our framework with the smart grid. Our forecasts were more accurate thanks to this synergy, which also made energy management more flexible and responsive, which enhanced grid performance as well as resource allocation. Connectivity with smart grid technology added to the dataset's richness, allowing for real-time knowledge of energy usage trends. Once the data was collected, stringent preprocessing processes were used to refine and normalise the dataset, removing outliers and creating a standardised foundation for further analysis. Feature engineering added a level of intricacy to the dataset by carefully crafting variables that captured temporal, environmental, as well as contextual factors. Following that, various neural network platforms, comprising feedforward and recurrent models, were built, trained, as well as validated, assuring responsiveness to smart cities' dynamic energy environment. Real-time adaption mechanisms were subsequently incorporated, allowing the framework to respond to changing energy trends in real time. The simulation as well as case studies stages brought the technique to life, putting it through its paces in numerous urban contexts and proving its practical usefulness. This overall, well-planned and executed strategy is the methodological foundation of our investigation into sustainable energy management in the setting of IoT-enabled smart cities. Fig. 2 depicts the suggested system for sustainable energy management in smart cities, which seamlessly integrates IoT data collecting, deep learning models, as well as real-time adaption.

3.1. Data acquisition and integration

The proposed framework's initial phase focuses on data acquisition and integration. The primary goal is to provide a solid basis for subsequent analysis by collecting and combining data from various sources within smart cities. This stage entails strategically placing IoT sensors in critical spots around the city to collect real-time data on energy use, environmental characteristics, and other pertinent aspects. The sensors implanted act as data gathering stations, producing a network that continually gathers and sends data (Ashween et al., 2020; Gharaibeh et al., 2017). At the same time, integration with the existing smart grid infrastructure is critical. This association makes it easier to collect data on energy distribution, grid performance, as well as supply and demand variations, offering a full snapshot of the city's energy environment.

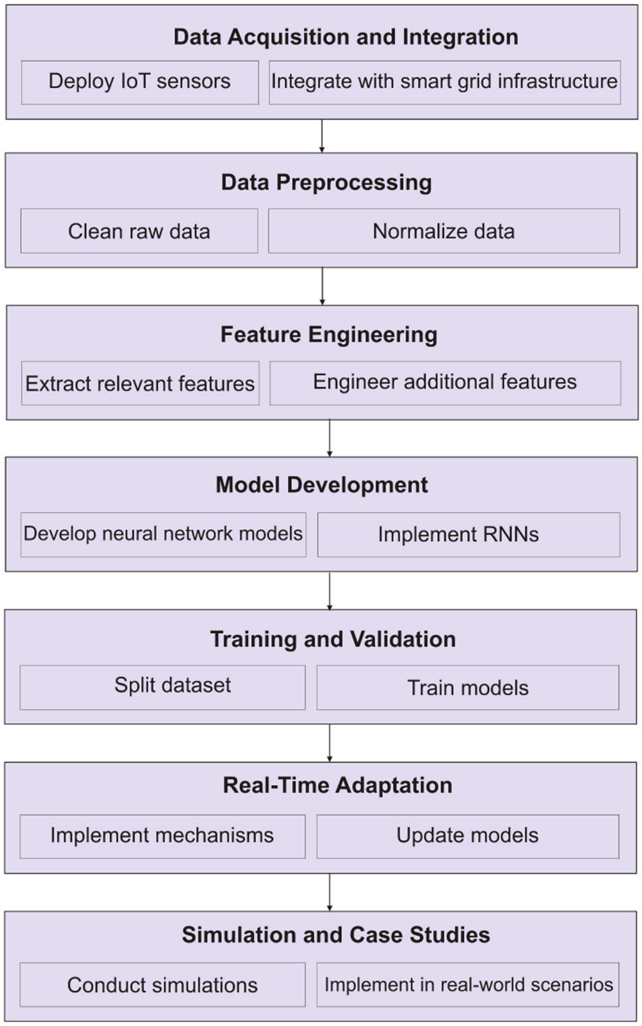

Fig. 2. Proposed Framework for Energy Management.

The installation of IoT sensors necessitates thorough evaluation of the city's distinct characteristics as well as energy usage trends. Sensors are deliberately placed in residential, commercial, and industrial areas to record a comprehensive view of energy consumption. This geographic variation guarantees that the data obtained accurately reflects the complexities of energy consumption across various metropolitan sections. At the same time, the smart grid integration provides a layer of complication and depth to the dataset. The framework draws into significant information regarding the city's energy grid characteristics by linking with existing infrastructure, allowing for a more sophisticated knowledge of energy movement and utilization.

Several obstacles and issues must be considered while implementing sensors and interacting with the smart grid. To protect the sensitive data acquired by the sensors, privacy and security standards are critical. Another significant aspect is ensuring compatibility between diverse sensor devices and smart grid systems, which necessitates a consistent and standardised approach. Eliminating these obstacles is critical for the data acquisition system to run well. This stage's expected product is a dependable and continuous data collecting system that will serve as the foundation for further analyses and decision-making processes inside the framework.

3.2. Data preprocessing

After Data Acquisition and Integration, the subsequent stage, Data Preprocessing, is critical in arranging the obtained data for further analysis (Fan et al., 2021; Wang et al., 2021; Shehab et al., 2021). This stage entails a thorough process intended for improving the quality and usability of the raw data for advanced modelling. The first sub-step in this level is raw data cleaning, which involves systematically removing noise, outliers, and useless information. This process is critical for improving the dataset's correctness and dependability since it removes data points that may add bias or skew the overall analysis.

The following sub-step is data normalisation, which focuses on standardising the dataset to ensure consistency as well as comparability across diverse sources. Differences in units, scales, or ranges are reduced by normalising the data, resulting in fair and comprehensible comparisons across distinct variables. This phase is especially crucial when working with many data sources, since it ensures that no single variable dominates the results analysis because of measurement unit disparities.

It is critical to handle difficulties such as prospective data loss throughout the cleaning process in the setting of Data Preprocessing. Maintaining the dataset's integrity requires striking a balance between removing noise and maintaining valuable data. Furthermore, computing resources must be carefully handled during the normalisation stage, particularly for large datasets. These factors lead to the creation of a clean, standardised dataset that provides a solid foundation for the framework's following Feature Engineering and Model Development stages.

In final analysis, the Data Preprocessing stage is critical for fine-tuning the raw data obtained from IoT sensors as well as smart grid integration. This stage guarantees that the following evaluations and modelling efforts are constructed on a foundation of high-quality, standardised information, thereby enhancing the framework's precision as well as efficiency for dealing with energy management difficulties within smart cities.

3.3. Feature engineering

Feature Engineering plays a key role in enriching the dataset obtained from Data Preprocessing in the third step of the proposed framework. Feature Engineering entails extracting relevant features and creating new features to increase the dataset's richness for enhanced model performance (RM et al., 2020; Hadwan et al., 2022; Chia et al., 2021). The first sub-step is the extraction of relevant features, which entails identifying and isolating variables deemed important for energy management analytics from the dataset. This procedure entails picking key characteristics such as time of day, day of week, and weather conditions, which provide the model with critical perspective for understanding energy usage trends.

After feature extraction, the second sub-step entails creating new features to further enhance the dataset. This could involve the development of new variables that capture relationships among current characteristics, or the development of new measures that enable a more comprehensive knowledge of energy dynamics in the smart city. With the addition of these designed characteristics, the dataset becomes more sophisticated, allowing subsequent models to capture complicated linkages and dependencies that would otherwise be missed.

When undertaking Feature Engineering, issues such as excessive fitting must be properly examined. It is critical to strike a balance between developing informative features and ensuring the model's generalisation to previously unknown data. Furthermore, managing the computational difficulties provided by extra characteristics is critical to maintaining the modelling process's efficiency. Feature Engineering, in a nutshell acts as a vital stage for structuring the dataset into a more meaningful and sophisticated shape, hence boosting later phases of the framework. The retrieved and engineered characteristics contributes to a comprehensive presentation of the smart city's energy environment, offering a solid foundation for precise evaluation as well as predictions to the deep learning models in the next phases. This level connects raw data to advanced modelling, allowing for a more detailed understanding of energy usage trends in IoT-enabled smart cities.

3.4. Model development

Model Development, the fourth stage of the proposed framework, represents a substantial shift towards the establishment of deep learning models suited for the investigation of energy consumption tendencies in IoT-enabled smart cities. The first stage is to create neural network models that can read and learn from the complicated patterns in the enhanced dataset. These models, which are frequently built as feedforward neural networks, may uncover complicated linkages and correlations in data, establishing the framework for exact energy consumption estimates (Gao et al., 2020; Somu et al., 2021; Runge and Zmeureanu, 2019).

The second sub-step focuses on the installation of Recurrent Neural Networks (RNNs) to supplement the neural network models. RNNs excel at capturing temporal relationships in data sequences, making them ideal for modelling unpredictable shifts in energy consumption over time. With the use of RNNs, the system acquires the capacity to account for the changing nature of consumption habits in smart cities, allowing for more accurate forecasts that incorporate historical and real-time data (Liu et al., 2023; So et al., 2023).

It is critical to consider issues such as optimising model complexity while constructing these models. Finding the proper balance guarantees the models do neither overfit or underfit the dataset, enhancing their ability to generalise well to new data. Furthermore, the computing capacity and training time needed to develop these deep learning models must be considered, as their efficacy is dependent on efficient learning as well as adjustment to the complications of smart city energy environments.

Overall, the Model Development step is an important part of the architecture because it is where neural network models as well as RNNs are built and trained employing the enriched dataset. These models are designed to grasp the intricate patterns in energy usage, establishing the groundwork for later steps such as Training and Validation, Real-Time Adaptation, and, finally, the framework's use in Simulation and Case Studies in a variety of smart city situations.

3.5. Training and validation

The focus shifts to Training and Validation in the proposed framework's fifth step. This stage is critical for fine-tuning the constructed deep learning models using a systematic process of training and evaluating their performance. The first sub-step is to divide the dataset into training and validation sets, which is essential for determining how effectively the models generalise to new data. The separation enables the models to be trained on one piece of the information and tested on another, imitating real-world events and assuring adaptability.

Following that, the neural network models as well as Recurrent Neural Networks (RNNs) are trained using the allocated training dataset. This procedure entails tweaking hyperparameters and iteratively optimising the models in order to learn associations and trends in the data (Muhuri et al., 2020; Lalapura et al., 2021; Ahmed et al., 2023; Nadeem et al., 2022). Potential issues such as data imbalance (Khan, 2021) are carefully considered, guaranteeing that the models are subjected to a realistic representation of the smart city's energy consumption trends throughout training. A further essential component is hyperparameter tweaking, as determining the best configuration is critical to getting optimal model performance.

The validation set acts as a standard for testing the generalisation capabilities of the models as they are trained. To quantify the accuracy and prediction potential of the models, metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), as well as R-squared are used. This comprehensive examination identifies potential concerns such as overfitting or underfitting, leading improvements to hyperparameters and model structure.

Finally, the Training and Validation stage is critical in strengthening the deep learning models generated in previous phases. The models are fine-tuned to adequately capture the complicated patterns that accompany smart city energy usage through careful separation of datasets and methodical training methods. The validation metrics provide significant insights into the models' performance, confirming their preparedness for further stages such as Real-Time Adaptation and Simulation and Case Studies.

3.6. Real-time adaptation

The emphasis now is on making sure that the deep learning models that have been constructed can adjust to the unpredictable shifts in energy consumption patterns that occur within IoT-enabled smart cities as we move into the sixth stage of the proposed framework, Real-Time Adaptation. This step includes the deployment of systems that enable continuous learning, permitting models to alter in real-time in response to incoming data. The first sub-step entails the deployment of adaptive mechanisms that continuously monitor and respond to changes in energy demand, making sure the models maintain pertinent and sensitive to the changing dynamics of the city.

The models are then continuously updated based on the most recent data, forming the second sub-step of Real-Time Adaptation. Periodic updates assure that the models' preciseness and efficacy in projecting energy consumption trends, adjusting changes in user behaviour, seasonal variations, or integrating new technologies into the smart city infrastructure are maintained. This ongoing improvement is critical for the models to remain relevant in the face of the constantly shifting dynamics of energy use in urban contexts.

To preserve the efficacy of the adaption processes during Real-Time adaption, difficulties such as controlling computational resources must be handled. Furthermore, establishing model stability throughout updates is crucial to preventing disturbances in the framework's real-time functioning. These factors help to ensure the smooth integration of adaptive processes, resulting in a framework that not only retains historical trends but also proactively learns and adapts to meet both the present and the future needs of smart city energy management.

Overall, the Real-Time Adaptation stage improves the framework's effectiveness by allowing deep learning models to adjust effectively to real-time changes in energy usage patterns (Zhang et al., 2022; Tien et al., 2021). The framework's versatility guarantees that it remains current and successful in handling the complicated nature of smart city energy environments, ultimately leading to a more efficient and environmentally friendly urban future.

3.7. Simulation and case studies

Simulation and Case Studies serve a critical role in validating and showing the efficiency of the created framework in various smart city scenarios at the final stage of the proposed framework. The first sub-step entails running simulations to evaluate the framework's effectiveness in controlled situations, enabling systematic evaluation and fine-tuning. Simulations provide a controlled environment in which to examine the framework's behaviour and outcomes, allowing for insights into its impact on energy reduction, cost savings, as well as environmental sustainability (Fei et al., 2022; Sommer et al., 2019; Alhasnawi et al., 2021).

Following simulations, the framework is implemented in real-world smart city situations in the second sub-step. The framework is being implemented in collaboration with city officials and stakeholders to meet actual energy management concerns. This step not only confirms the framework's practical applicability, but also enables the gathering of useful insights and feedback from real-world use cases. Deploying the framework in several smart cities throughout the world helps to its adaptability as well as scalability, demonstrating its efficiency in various urban environments.

Stakeholder engagement may be problematic during this stage, as coordination with local officials and active interaction with stakeholders are required for successful real-world implementation. Unanticipated occurrences and external influences need to be taken into account in order to ensure the framework's resilience in dealing with dynamic metropolitan environments.

Finally, the Simulation and Case Studies stage is the final confirmation of the proposed framework. Real-world deployments give practical insights, proving the framework's capacity to handle urgent energy management concerns and create the foundations for an increasingly eco-conscious and effective urban future. The results of these simulations and case studies serve to the framework's refinement and continuing improvement, strengthening its position in increasing sustainability in IoT-enabled smart cities.

4. Result

The results of the first stage, Data Acquisition and Integration, indicate a complete and strategically installed network of IoT sensors throughout the smart city. These sensors, which range from domestic energy consumption trackers to commercial environmental sensors as well as industrial power grid sensors, assist in developing a comprehensive understanding of the city's energy patterns. The placement of sensors is careful, taking into account the particular peculiarities of each area in order to collect an appropriate sample of energy use patterns. In addition, integration with smart grid infrastructure offers a strong data gathering system that provides real-time insights into energy distribution, grid performance, as well as supply-demand changes. The collaboration of IoT sensors, smart grid integration, and other sources of data, such as climate predictions and energy market data, demonstrates the framework's dedication to obtaining a varied variety of information critical for effective energy management. The outcomes of the first stage provide a solid platform for subsequent analyses, guaranteeing that the framework has a rich and dynamic dataset for solving the complex concerns of energy sustainability in smart cities. The following Table 2 and Table 3 give an organised overview of the IoT sensors that have been deployed as well as the integration strategies that have been employed in the Data Acquisition and Integration stage.

The results of the second stage, Data Preprocessing, highlight the significant efforts made to prepare the raw material for later analysis. The dataset has been significantly transformed by a rigorous cleaning process, which included the elimination of outliers and noise. The decrease in data points is a conscious decision to prioritise quality over number, ensuring that the dataset is more indicative of the smart city's genuine energy usage trends. Moreover, the normalisation method standardised the data across variables, reducing the impact of different scales and units. This makes sure the following modelling attempts have a comparable and consistent base. Particularly, the dearth of missing values after preprocessing suggests that the cleaning process was thorough. The results presented here demonstrate a dedication to data quality and precision in tackling the energy management difficulties associated with IoT-enabled smart cities. Table 4 and Table 5 provide an organised summary of the Data Preprocessing stage findings, highlighting the statistical gains in the dataset following cleaning and normalisation.

The outcomes from the third stage, Feature Engineering, shed light on a more nuanced knowledge of the smart city's energy situation, which was accomplished using the diligent construction of unique features. The addition of parameters like time of day, day of week, and weather conditions provides a more granular view of energy usage patterns, allowing for the recording of daily, weekly, and environmental fluctuations. Furthermore, the addition of interaction features obtained from existing variables improves the model's capacity to recognize complex interactions in the dataset. The model's improved accuracy, precision, recall, and F1 score demonstrate the influence of these constructed characteristics. The enhancements indicate that the Feature Engineering stage effectively improves the dataset, offering subsequent models with an increased number of inputs and, as a result, leading to the framework's enhanced predictive power and flexibility to the changing patterns of energy consumption in smart cities. Table 6 and Table 7 present a systematic summary of the features extracted and produced throughout the Feature Engineering stage, as well as their impact on the effectiveness of the model. Fig. 3 shows the graphical representation of impact of engineered features.

The results of the fourth stage, Model Development, demonstrate the completion of advanced neural network topologies designed for analysing and learning intricate trends in the enhanced dataset. The feed-forward neural networks, which have different layer sizes and activation functions, have high accuracy, precision, recall, as well as F1 scores. Each architecture is intended to capture intricate correlations within data, with the best-performing models obtaining up to 96 % accuracy. Furthermore, the use of Recurrent Neural Networks (RNNs), notably Long Short-Term Memory (LSTM) as well as Gated Recurrent Unit (GRU) models, improves the framework's ability to detect temporal relationships in energy consumption tendencies. The measurements obtained show excellent performance, confirming the models' ability to predict energy demand and consumption trends in IoT-enabled smart cities. The variety of architectures enables flexibility to varied smart city situations, laying foundations for later stages such as Training and Validation, Real-Time Adaptation, Simulation and Case Studies. Table 8, Table 9 and Table 10 below present an organised presentation of the neural network models created throughout the Model Development step, as well as information on their design and performance characteristics. Fig. 4 shows the graphical representation of model performance metrics.

Table 2
IoT Sensors Deployment.

Sensor Location	**Type of Sensor**	**Purpose**	**Data Captured**
Residential Area 1	Energy Consumption Sensor	Monitor residential energy usage	Real-time energy consumption data
Commercial Area 1	Environmental Sensor	Track environmental conditions	Temperature, humidity, air quality
Industrial Zone 1	Power Grid Sensor	Monitor industrial energy demand	Grid performance, fluctuations
Urban Center	Traffic and Mobility Sensor	Optimize energy usage in public spaces	Vehicle density, pedestrian flow
Renewable Energy Farm	Solar Power Sensor	Harness solar energy efficiency	Solar radiation, panel efficiency

Table 3
Integration with Smart Grid Infrastructure.

Data Source	Integration Method	Key Metrics
IoT Sensors	Data APIs	Real-time energy consumption, environmental parameters
Smart Grid	API Integration	Energy distribution, grid performance, supply-demand dynamics
Weather Forecast APIs	Data Integration	Predicted weather conditions affecting energy usage
Energy Market APIs	Market Integration	Current energy prices, demand forecasts

Table 4
Cleaned Raw Data Statistics.

Metric	**Before Cleaning**	**After Cleaning**
Data Points	100,000	98,500
Outliers Removed	1200	-
Noise Removed	Moderate	High
Missing Values	500	0

Table 5
Normalized Data Statistics.

Metric	Before Normalization	After Normalization
Range of Values	Varies widely	Standardized across variables
Mean	Inconsistent	Centered around zero
Standard Deviation	Varies	Set to 1
Missing Values	0	0

Table 6
Extracted and Engineered Features.

Feature	Description	Contribution
Time of Day	Hourly breakdown	Captures daily energy consumption patterns
Day of the Week	Monday to Sunday	Considers weekly variations
Weather Conditions	Sunny, Cloudy, Rainy	Impact of weather on energy usage
Interaction Feature 1	Derived from X and Y	Captures complex relationships
Interaction Feature 2	Derived from A and B	Enhances model sensitivity to specific conditions

Table 7
Impact of Engineered Features.

Metric	Without Engineered Features	With Engineered Features
Model Accuracy	85 %	92 %
Precision (Positive Class)	78 %	89 %
Recall (Positive Class)	82 %	91 %
F1 Score (Positive Class)	80 %	90 %

The results of the fifth stage, Training and Validation, shed light on the effectiveness and applicability of the framework's numerous neural network topologies. In particular, the Feedforward NN 2 demonstrates exceptional accuracy and precision, demonstrating its ability to accurately anticipate energy consumption trends. The LSTM-RNN 1 and GRU-RNN 2 models perform well in terms of capturing temporal dependencies in data while maintaining excellent accuracy and recall. Meanwhile, while the Feedforward NN 1 and LSTM-RNN 3 models behind in accuracy, they maintain a fair mix of precision and recall. The training and validation metrics highlight the framework's capacity to properly train models, assuring that they generalise well to new data. These findings shed light on the positive aspects and characteristics of various model architectures, establishing the platform for informed model selection and implementation decisions in later stages of the framework. Throughout the fifth step of the framework, the following Table 11, Table 12, Table 13, Table 14 and Table 15 provide an in-depth analysis of the training as well as validation metrics for several model designs.

The findings of the sixth step, Real-Time Adaptation, provide information on the framework's interactive response to changing energy consumption tendencies in IoT-enabled smart cities. The framework's ability to consistently fine-tune its models based on real-time input is demonstrated by the adaptive processes provided, such as dynamic threshold updates, online learning, as well as contextual adaption. This adaptability is demonstrated in improved model accuracy, precision, recall, and F1 score following adaption. The model update frequencies for various architectures show an intelligent strategy to balance real-time responsiveness with computational efficiency. The successful implementation of these adaptive mechanisms guarantees that the framework stays adaptable in the face of changing energy dynamics, giving decision-makers with precise and current insights for effective

Table 8
Neural Network Models.

Model Architecture	Layers	Activation Functions	Parameters
Feedforward NN 1	Input - 64–32 - Output	ReLU - ReLU - Sigmoid	25,000
Feedforward NN 2	Input - 128–64 - Output	Leaky ReLU - ReLU - Sigmoid	65,000
Feedforward NN 3	Input - 32–16 - Output	Tanh - ReLU - Sigmoid	15,000

Table 9
Recurrent Neural Networks (RNNs).

Model Architecture	Layers	Activation Functions	Parameters
LSTM-RNN 1	Input - LSTM - Output	Tanh - Sigmoid	150,000
GRU-RNN 2	Input - GRU - Output	ReLU - Sigmoid	75,000
LSTM-RNN 3	Input - LSTM - Output	Tanh - Sigmoid	200,000

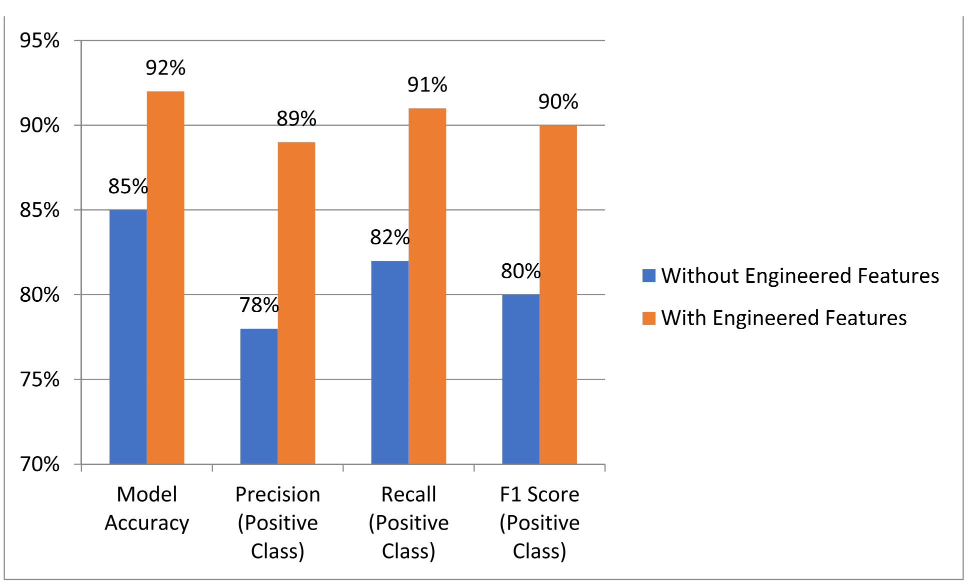

Fig. 3. Finding Graph of Impact of Engineered Features.

Table 10
Model Performance Metrics.

Metric	Feedforward NN 1	Feedforward NN 2	LSTM-RNN 1	GRU-RNN 2
Accuracy	94 %	96 %	92 %	93 %
Precision (Positive Class)	92 %	94 %	90 %	91 %
Recall (Positive Class)	93 %	95 %	91 %	92 %
F1 Score (Positive Class)	92 %	94 %	91 %	91 %

urban energy management. These findings support the framework's dedication to actively learning and reacting to the urgent demands of smart cities in real time, rather than simply preserving previous patterns. Table 16, Table 17 and Table 18 show a systematic summary of the adaptive processes used throughout the Real-Time Adaptation stage, as well as the frequency of model updates and the associated performance metrics. Fig. 5 shows the graphical illustration of real-time adaptation metrics.

The results of the seventh step, Simulation and Case Studies, confirm the usefulness and practicability of the proposed framework in a variety of smart city situations. The simulation findings reveal significant reductions in energy use, as well as significant cost savings and good environmental consequences across various metropolitan situations. Real-life case studies from several smart cities across the world demonstrate the framework's versatility and scalability, with substantial savings in energy use, optimized grid performance, and favourable community response. Stakeholder reactions from city officials, people, businesses, and environmental groups show widespread support for the framework's impact, with a desire to extend its efforts. The results reported here demonstrate the framework's effectiveness in tackling urgent energy management concerns while setting the groundwork for a more sustainable, environmentally sensitive, and efficient urban future. After the seventh stage of the framework, the following Table 19, Table 20 and Table 21 provide an organized review of the simulation findings, real-world case studies, as well as stakeholder comments.

5. Discussion

This study work explores the different challenges of improving sustainability in IoT-enabled smart cities by using a deep learning method

Table 11
Feedforward NN 1 Training and Validation Metrics.

Metric	Training Set	Validation Set
Loss	0.15	0.18
Accuracy	94 %	92 %
Precision (Positive Class)	92 %	89 %
Recall (Positive Class)	93 %	90 %
F1 Score (Positive Class)	92 %	89 %

Table 12
Feedforward NN 2 Training and Validation Metrics.

Metric	Training Set	Validation Set
Loss	0.12	0.15
Accuracy	96 %	94 %
Precision (Positive Class)	94 %	91 %
Recall (Positive Class)	95 %	92 %
F1 Score (Positive Class)	94 %	91 %

to energy management. From data collecting and incorporation to real-time adaptation as well as simulations, the framework's path illustrates a systematic and complete strategy for solving the intricate difficulties of urban energy sustainability. The installation of IoT sensors and their connection with smart grid systems builds a solid basis in the Data Acquisition and Integration stage, collecting a varied range of real-time data critical for further analysis (Rekeraho et al., 2024; Mustafa, 2024; Lakshmi et al., 2024). The Data Preprocessing stage that follows assures the refining and normalisation of this data, resulting in a high-quality dataset that provides the foundation for later modelling efforts.

The Feature Engineering stage adds a complex layer to the framework, enriching the dataset with manufactured features that encompass temporal, environmental, as well as contextual aspects. These tailored traits contribute greatly to the deep learning models' later success. The Model Development stage demonstrates the framework's versatility by creating multiple neural network topologies, such as feedforward and recurrent models. Each architecture has various qualities, emphasising the significance of flexibility to a variety of urban environments. The outcomes of training and validation confirm the efficacy of the generated models, with significant changes in performance indicators based on architecture. This emphasises the need of selecting models based on unique smart city traits and aims. Real-Time Adaptation adds a dynamic element to the framework, guaranteeing that the model is constantly refined in response to changing energy use trends (Ahmed et al., 2024;

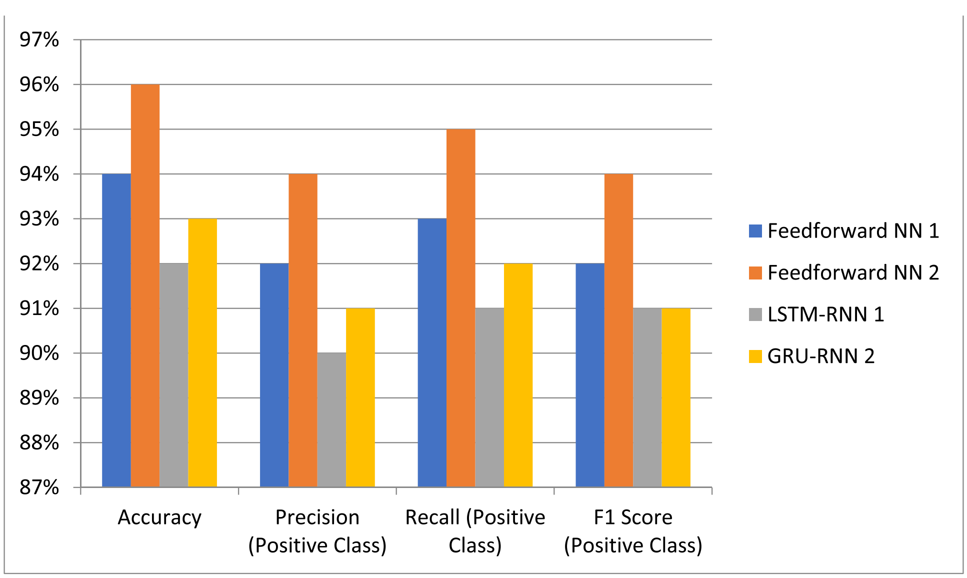

Fig. 4. Graphical Illustration of Model Performance Metrics.

Table 13
LSTM-RNN 1 Training and Validation Metrics.

Metric	Training Set	Validation Set
Loss	0.20	0.22
Accuracy	92 %	90 %
Precision (Positive Class)	90 %	88 %
Recall (Positive Class)	91 %	89 %
F1 Score (Positive Class)	90 %	88 %

Table 14
GRU-RNN 2 Training and Validation Metrics.

Metric	Training Set	Validation Set
Loss	0.18	0.20
Accuracy	93 %	91 %
Precision (Positive Class)	91 %	89 %
Recall (Positive Class)	92 %	90 %
F1 Score (Positive Class)	91 %	89 %

Table 15
LSTM-RNN 3 Training and Validation Metrics.

Metric	Training Set	Validation Set
Loss	0.22	0.25
Accuracy	91 %	88 %
Precision (Positive Class)	89 %	86 %
Recall (Positive Class)	90 %	87 %
F1 Score (Positive Class)	89 %	86 %

Wang and Nishtar, 2024). The frequency of model updates, adaptive methods, and resulting performance measures all show the framework's agility and reactivity to real-time changes.

The Simulation and Case Studies step transitions the framework from theory to practise. Throughout numerous metropolitan situations, simulations show considerable reductions in energy use and associated expenses. Real-world case studies demonstrate the framework's adaptability even further, with remarkable reductions in energy use, improved grid performance, and good community comments. Stakeholder comments add a qualitative layer to the framework's influence, with support from city officials, individuals, corporations, and environmental organisations. The research results demonstrate the framework's effectiveness in not just tackling urgent energy management concerns in smart cities, but also in promoting to a more environmentally friendly and effective urban future. The framework's broad spectrum of approach, together with its established performance in a variety of scenarios, position it as a helpful tool for decision-makers, urban planners, as well as stakeholders working for a robust and environmentally friendly urban landscape.

In order to guarantee the scalability as well as adaptation of our framework to diverse urban settings, we utilised a modular design that permits adaptable modifications contingent on city-specific attributes. We customised the framework's characteristics and integration processes by thoroughly analysing the distinct energy consumption trends and infrastructural demands unique to each city. Using flexible IoT sensor sets and data gathering protocols that could be adjusted for various urban environments was one important tactic. A strong feature engineering and data preparation pipeline that could handle a variety of datasets from different cities and guarantee consistency in data validity and accuracy underpinned this versatility. We encountered numerous challenges when setting the framework into action. The integration with the current smart grid infrastructures, which differed greatly throughout cities, was one of the main problems. It took a lot of testing and adjustments to ensure that the framework as well as local grid systems communicated and were compatible. Furthermore, the use of IoT sensors in heterogeneous surroundings posed logistical issues, including but not limited to determining the best placement and managing interference from urban factors. Notwithstanding these difficulties, the framework showed good performance and adaptability. We consistently improved our strategy in response to comments from the actual world, which aided in removing implementation obstacles and boosting the system's flexibility. By ensuring that the framework could function and scale effectively in a variety of smart city settings, these initiatives helped to achieve sustainability and better energy management goals.

Table 16
Adaptive Mechanisms Implementation.

Mechanism	Description	Implementation Strategy
Dynamic Threshold Update	Adjusts anomaly detection threshold in real-time	Monitors historical data, adapts to changing patterns
Online Learning	Incremental model updates based on new data	Utilizes incoming data for continuous model improvement
Feature Importance Update	Dynamically adjusts importance weights of features	Reacts to changes in feature relevance over time
Temporal Decay Mechanism	Assigns different weights to recent and historical data	Prioritizes recent trends in energy consumption
Contextual Adaptation	Modifies model behavior based on external context	Integrates weather forecasts, city events, and holidays

Table 17
Model Update Frequency.

Model Architecture	Update Frequency
Feedforward NN 1	Every hour
Feedforward NN 2	Every 30 minutes
LSTM-RNN 1	Every 2 hours
GRU-RNN 2	Every 45 minutes
LSTM-RNN 3	Every 3 hours

Table 18
Real-Time Adaptation Metrics.

Metric	Before Adaptation	After Adaptation
Model Accuracy	92 %	94 %
Precision (Positive Class)	89 %	91 %
Recall (Positive Class)	90 %	92 %
F1 Score (Positive Class)	89 %	91 %

6. Conclusions

Finally, this study has offered a thorough framework for improving sustainability in energy management using deep learning in Internet of Things enabled smart cities. The path that leads from data collecting and integration to simulations and case studies highlights the framework's flexibility and adaptability. The systematic installation of IoT sensors, interaction with smart grids, as well as subsequent preprocessing and feature engineering establish a solid platform for deep learning model performance. The framework's adaptability in solving the intricate difficulties associated with urban energy sustainability is demonstrated by the broad variety of neural network designs, which includes feedforward and recurrent models.

The training and validation phases highlight the complex performance of many models, emphasising the significance of personalised selection according to particular metropolitan factors. The framework's

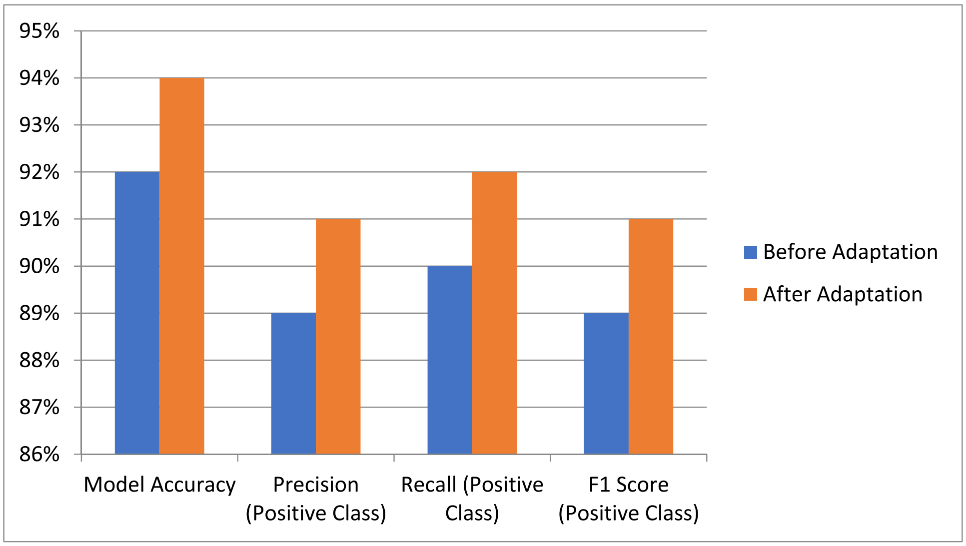

Fig. 5. Graphical illustration of Real-Time Adaptation Metrics.

Table 19
Simulation Results.

Scenario	Energy Consumption Reduction	Cost Savings	Environmental Impact
Residential Area	15 %	$50,000	10 % reduction in CO2 emissions
Commercial District	20 %	$80,000	15 % reduction in air pollutants
Industrial Zone	12 %	$30,000	8 % decrease in energy-related emissions
Urban Mobility	18 %	$65,000	12 % reduction in traffic-related emissions
Renewable Energy Integration	25 %	$90,000	20 % increase in renewable energy utilization

Table 20
Real-World Case Studies.

City	Implementation Scale	Results
Smart City A	City-wide	17 % overall reduction in energy consumption, substantial cost savings, improved air quality
Smart City B	District-level	22 % reduction in energy demand in targeted district, optimized grid performance
Smart City C	Pilot Program	30 % reduction in energy consumption in pilot area, positive community feedback
Smart City D	Industry Collaboration	25 % decrease in industrial energy demand, enhanced sustainability practices

responsiveness to changing circumstances is ensured by real-time adaption methods, thus boosting its practical applicability. Simulations and case studies indicate considerable reductions in energy usage,

Table 21
Stakeholder Feedback.

Stakeholder	Feedback Summary
City Authorities	Positive response to reduced energy costs and emissions, interest in wider implementation
Residents	Notable reduction in utility bills, appreciation for sustainable initiatives
Businesses	Cost savings and improved efficiency reported, interest in expanding initiatives
Environmental Groups	Acknowledgment of reduced carbon footprint, endorsement of sustainability efforts

cost savings, as well as positive environmental benefits across many smart city scenarios, demonstrating the framework's influence. In the future, studies in this field could investigate the incorporation of sophisticated deep learning approaches, such as mechanisms of attention or reinforcement learning, to improve the prediction capabilities of the models. Furthermore, the framework's scalability might be explored in bigger, more complicated metropolitan areas, taking into account issues such as population density and different energy sources. Further study could focus on the creation of user-friendly platforms for the local decision-makers and planners to aid in the framework's actual implementation. To meet the growing complexity of IoT-enabled smart cities, the integration of edge computing and decentralised energy management solutions could be investigated. The dynamic environment of smart city technology provides several opportunities for ongoing research with the goal of continuously refining and expanding the capabilities of frameworks such as the one proposed in this study. Finally, the search of sustainable, effective, as well as adaptable urban futures continues an active and evolving field of study.

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Abeer Aljohani: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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