CHAPTER TWO

LITERATURE REVIEW

2.1 Chapter Overview

This chapter is dedicated to a thorough and critical analysis of prior scholarly and technical work related to the development, simulation, and implementation of Internet of Things (IoT)-driven systems for energy monitoring and forecasting within the context of urban infrastructure. It delves into recent technological advancements that have significantly reshaped how energy is managed, monitored, and predicted in smart city environments. Special emphasis is placed on the deployment and performance of forecasting models—such as Facebook Prophet and Long Short-Term Memory (LSTM) networks—that are commonly utilized in time-series prediction tasks associated with energy consumption. Additionally, the review explores the evolution and significance of simulation tools and platforms that enable city-scale modeling and validation of such systems prior to real-world deployment. Beyond the technological perspectives, this chapter also focuses on contextual challenges relevant to underdeveloped or developing urban settings, with particular reference to Nigerian cities where data availability is limited and infrastructural resources are often insufficient. It examines how these constraints affect system design choices, data modeling approaches, and deployment strategies. Drawing on a combination of peer-reviewed research, simulation-based experiments, and case studies, the chapter synthesizes both the theoretical frameworks and practical limitations that shape the adoption of predictive energy systems using IoT technologies.

Ultimately, the insights gathered through this review serve a dual purpose: first, to highlight existing knowledge gaps and contextual challenges that need to be addressed; and second, to justify the need for a customized, scalable, and simulation-oriented IoT solution tailored to the unique conditions of urban centers in developing regions. This justification forms the conceptual and practical foundation for the system proposed in this research.

2.2 State-of-the-Art

The landscape of urban energy management has undergone a profound transformation over the past two decades, driven by the convergence of Internet of Things (IoT) technologies, intelligent forecasting models, and edge-centric computing paradigms. The need to enhance energy efficiency, minimize losses, and optimize demand forecasting has sparked substantial research into smart grids, autonomous monitoring systems, and predictive analytics frameworks.

2.2.1 Global Evolution of Smart Energy Monitoring

The evolution of smart energy monitoring systems has undergone significant transformations over the past two decades, shaped by technological innovation, changing user demands, and the increasing need for energy sustainability in urban environments. In the early 2000s through to around 2010, energy management systems were largely dominated by traditional Supervisory Control and Data Acquisition (SCADA) architectures. These legacy systems, while effective for industrial-scale monitoring, operated in a highly centralized and rigid manner. They offered limited flexibility for integration with other technologies and virtually no interaction with end consumers. The scalability of SCADA frameworks was insufficient to meet the growing complexity of energy demands in modern cities, especially with the emergence of distributed energy resources and smart grid concepts. Consequently, their application in dynamic and heterogeneous urban contexts remained constrained.

Between 2011 and 2016, the landscape began to shift with the widespread deployment of smart meters and the introduction of cloud-based energy dashboards. These systems significantly improved consumer-level visibility and allowed centralized authorities to remotely monitor energy usage patterns in real time. This period marked a key transition from passive to interactive energy consumption, enabling utilities and consumers to make more informed decisions. However, while these solutions improved transparency and control, they also introduced new challenges. Chief among them were latency issues due to the reliance on centralized cloud servers, and growing concerns over data privacy and security, as sensitive consumption information was increasingly transmitted over public networks.

The period from 2017 to 2022 witnessed the integration of Internet of Things (IoT) technologies into energy monitoring systems, representing a major leap in both capability and architecture. IoT-enabled solutions utilized a network of distributed sensors, microcontrollers, and wireless communication protocols such as ZigBee and LoRaWAN to facilitate real-time data acquisition and processing. These systems shifted the paradigm from centralized monitoring to decentralized, edge-oriented processing. As a result, energy usage data could be captured, analyzed, and acted upon at or near the source, reducing latency and bandwidth demands. During this era, simulation frameworks such as iFogSim (Gupta et al., 2016) and IoTNetSim (Salama et al., 2019) were developed to help researchers and practitioners model, simulate, and evaluate the performance of IoT-based energy systems in various environmental and infrastructural scenarios. These tools played a crucial role in validating architectural choices and understanding tradeoffs in system design before actual deployment.

From 2023 to the present, the focus in smart energy monitoring has shifted toward leveraging artificial intelligence (AI) and advanced machine learning algorithms for predictive analytics and demand forecasting. The convergence of AI with IoT, along with the adoption of hybrid cloud-edge architectures, has enabled more intelligent, adaptive, and autonomous energy systems. Modern solutions aim to be not only technologically advanced but also economically viable for low-resource environments. Studies such as Aslam et al. (2021) have explored intelligent demand-response frameworks capable of dynamically adjusting to fluctuating energy needs, thereby improving grid resilience. Additionally, researchers like Nikpour et al. (2023) have demonstrated the efficacy of deep learning models, particularly Long Short-Term Memory (LSTM) networks, in modeling complex, non-linear energy consumption patterns. These innovations are particularly relevant in the global effort to design scalable and context-aware systems for smart city energy management, especially in underserved regions where infrastructure may be limited and cost-effectiveness is paramount.

2.2.2 Technological Paradigm Shifts

The field of smart energy monitoring has been marked by several profound technological paradigm shifts that have redefined how energy systems are designed, deployed, and managed. One of the most significant transformations is the shift from centralized architectures to decentralized infrastructures. Traditional energy management systems were heavily reliant on central servers and data centers for processing and decision-making. While such centralization facilitated administrative control, it also introduced latency, bottlenecks, and single points of failure. In response to these limitations, modern energy systems have increasingly adopted edge and fog computing frameworks. Edge computing allows data to be processed closer to the source—at sensors or local gateways—thereby reducing the time taken for analysis and action. Fog computing extends this model by providing intermediate processing nodes between the edge and the cloud, which improves system scalability and fault tolerance. These decentralized architectures enhance the ability of energy systems to operate autonomously in real time, even in the face of network disruptions or cloud service unavailability. This architectural flexibility is especially beneficial for applications requiring immediate response, such as real-time demand management and fault detection.

Another critical paradigm shift has occurred in the transition from retrospective monitoring to predictive energy management. In earlier generations of energy systems, historical data was primarily used for reporting past trends and generating static consumption summaries. While useful for analysis, these approaches lacked the capability to anticipate future events or adapt to dynamic conditions. Contemporary systems now emphasize predictive capabilities enabled by advanced time series forecasting models. Algorithms such as Prophet, developed by Taylor and Letham (2018), and Long Short-Term Memory (LSTM) neural networks have become prevalent due to their ability to model non-linear dependencies and temporal patterns in energy consumption data. These models offer significant improvements in forecasting accuracy, scalability, and adaptability across various use cases. Their integration into IoT-based systems has empowered energy providers and policymakers to make proactive decisions, optimize energy distribution, and implement effective demand-response strategies—ultimately enhancing grid stability and operational efficiency.

A further and equally transformative shift is the move from uniform, one-size-fits-all system designs to context-aware deployment strategies. Initial implementations of smart energy systems often followed standardized templates developed in technologically advanced environments, with minimal adaptation to local conditions. However, emerging research has highlighted the limitations of such an approach, particularly in developing regions where energy infrastructures are shaped by a unique combination of technical, social, and economic constraints. In contexts like Sub-Saharan Africa or parts of South Asia, challenges such as unreliable power supply, sparse or poorly maintained sensor networks, and diverse user behavior patterns can significantly impact the functionality and reliability of energy monitoring systems. As a result, recent innovations now emphasize the need for context-specific customization—tailoring both hardware and software solutions to fit local environmental conditions, resource availability, and user requirements. This shift toward contextual intelligence ensures not only improved system performance but also increased sustainability and user adoption in resource-constrained settings. Together, these technological paradigm shifts—from centralization to decentralization, from static monitoring to dynamic forecasting, and from uniformity to contextual responsiveness—are collectively reshaping the future of smart energy systems. They reflect a growing recognition of the importance of adaptability, real-time intelligence, and inclusivity in designing next-generation urban energy infrastructures

2.2.3 Urbanization and Developing Country Context

The domain of smart energy monitoring has undergone a series of transformative technological paradigm shifts that have fundamentally reshaped the design, deployment, and operational logic of modern energy systems. Foremost among these transformations is the transition from centralized architectures to decentralized infrastructures. Historically, energy management frameworks depended heavily on centralized servers and data centers to execute processing tasks and facilitate system-wide decision-making. Although such centralized systems enabled administrative oversight and streamlined control, they were inherently limited by latency issues, vulnerability to single points of failure, and limited adaptability in distributed urban environments. In response to these structural shortcomings, the field has progressively adopted edge and fog computing paradigms. Edge computing brings computational capabilities closer to data sources, such as sensors and local gateways, thereby enabling faster data processing and near-instantaneous response to critical events. Complementing this, fog computing provides intermediate layers of computation between the edge and cloud layers, offering enhanced scalability, resilience, and load-balancing capabilities. Together, these decentralized models empower energy systems to function with greater autonomy and reliability, even in scenarios where network connectivity is unstable or cloud services are temporarily inaccessible. This evolution is particularly crucial for real-time applications such as dynamic demand-response management, anomaly detection, and localized load balancing.

Another pivotal shift is the movement from retrospective data monitoring to forward-looking predictive energy management. Traditional systems largely focused on historical analysis, utilizing stored consumption records to generate static reports and descriptive analytics. While valuable for post-hoc assessments, these legacy approaches lacked the capacity to anticipate future trends or adapt proactively to evolving consumption patterns. In contrast, contemporary energy systems leverage advanced forecasting techniques to enable intelligent, anticipatory decision-making. Notable among these are time series models such as Prophet, introduced by Taylor and Letham (2018), and deep learning-based Long Short-Term Memory (LSTM) neural networks. These tools have proven highly effective in modeling complex, nonlinear, and seasonally variant energy usage behaviors. Their adaptability and forecasting accuracy make them indispensable in scenarios requiring granular load prediction, peak demand estimation, and adaptive scheduling of energy resources. By embedding these algorithms within IoT-enabled platforms, energy providers can implement responsive strategies that optimize grid performance, reduce operational costs, and enhance consumer satisfaction.

Equally transformative is the progression from uniform, standardized system designs toward deployment models that are increasingly context-aware and environment-specific. Early smart energy systems were frequently developed in technologically advanced nations and subsequently applied to other regions with minimal customization. However, this generalized approach has proven inadequate in regions characterized by infrastructural fragility, socio-economic variability, and environmental unpredictability. In developing contexts such as Sub-Saharan Africa and parts of South Asia, localized constraints—including inconsistent electricity supply, limited broadband connectivity, fragmented sensor networks, and culturally rooted consumption behaviors—pose significant challenges to system performance and sustainability. Consequently, contemporary research and development efforts now prioritize the design of context-sensitive solutions that align with local realities. These efforts encompass both hardware adaptations—such as low-power sensors, solar-powered gateways, and ruggedized edge devices—and software innovations that incorporate regional usage patterns, adaptive fault-tolerance, and culturally informed user interfaces. This paradigm shift toward contextualization ensures that energy monitoring systems are not only technologically sound but also socioeconomically relevant and sustainable over the long term. Collectively, these shifts—from centralized to distributed computation, from passive data collection to intelligent forecasting, and from generic to localized implementations—signal a new era in the evolution of smart energy systems. They underscore the growing importance of adaptability, responsiveness, and contextual intelligence in building next-generation energy infrastructures that are both resilient and inclusive. By aligning technological innovation with real-world complexity, these paradigm shifts pave the way for sustainable energy solutions that can be effectively scaled across diverse urban and regional landscapes.

2.2.4 Summary of Current Trends

The literature reveals a clear and well-documented trajectory in the evolution of energy management systems—from rudimentary, passive observation mechanisms to sophisticated, predictive, and adaptive energy ecosystems. This transformation reflects broader technological advancements and growing demands for efficiency, sustainability, and resilience in energy use. In earlier models, energy systems primarily functioned as monitoring tools that recorded historical consumption patterns without offering real-time insight or future-oriented functionality. However, as the integration of Internet of Things (IoT) devices, artificial intelligence (AI), and machine learning algorithms has matured, energy infrastructures have shifted toward intelligent ecosystems capable of not only monitoring but also predicting and responding to dynamic changes in demand and supply. In high-income countries, this shift has been embraced at scale, facilitated by advanced digital infrastructure, strong regulatory frameworks, and robust investments in smart grid technologies. These nations have developed and deployed large-scale, fully integrated energy systems that incorporate real-time sensing, automated control, and data-driven forecasting to optimize grid performance and reduce energy wastage. Moreover, widespread access to high-speed internet, reliable electricity, and cloud infrastructure enables seamless implementation of distributed computing paradigms and sophisticated predictive analytics, such as those powered by LSTM networks or hybrid models.

In contrast, many low- and middle-income countries (LMICs) are still in the nascent stages of adopting such innovations. These regions often face significant barriers—including inconsistent power supply, limited connectivity, underdeveloped sensor networks, and budgetary constraints—that impede the deployment of fully automated energy infrastructures. Nevertheless, the growing interest in digital transformation and the need to address pressing energy challenges are driving a gradual shift toward smarter systems. Within this context, simulation-based approaches and modular system design emerge as not merely advantageous, but essential. Simulation tools allow stakeholders in LMICs to model and test various configurations, algorithms, and deployment scenarios in a risk-free virtual environment before committing to full-scale implementation. This reduces the cost and complexity of experimentation and supports evidence-based decision-making. Modular design, on the other hand, enables flexible system development that can be tailored to suit the specific needs, capacities, and constraints of different urban and rural environments. By structuring energy solutions into interchangeable and scalable components, practitioners can incrementally deploy, upgrade, or adapt systems based on available resources and evolving local requirements. This approach supports phased adoption and allows for gradual technology integration—aligning well with the infrastructural realities of many developing regions. Together, these strategies not only bridge the technological gap between high-income and lower-income settings but also promote sustainable innovation by emphasizing accessibility, scalability, and contextual relevance. The emphasis on simulation and modularity, as revealed in current literature, underscores a critical insight: that the future of global energy management depends not only on cutting-edge technology but also on adaptable, inclusive design principles that can empower a broader range of communities to participate in the energy transition.

2.3 Literature Review

2.3.1 IoT-Based Energy Monitoring

The integration of the Internet of Things (IoT) into energy monitoring systems has emerged as a transformative force in modern energy management, enabling real-time visibility, improved decision-making, and greater operational efficiency. IoT-based energy monitoring systems consist of interconnected devices—such as sensors, actuators, smart meters, and gateways—that continuously collect and transmit data related to energy usage, environmental conditions, and system performance. This continuous flow of data allows for dynamic monitoring, early detection of anomalies, and fine-grained control of energy distribution networks. According to Aslam et al. (2021), smart energy infrastructures enhanced by IoT technologies have significantly contributed to reducing energy inefficiencies and operational waste. By leveraging real-time data acquisition and machine-to-machine communication, these systems offer utilities the ability to optimize load balancing, prevent energy leakage, and reduce peak demand through intelligent scheduling and automated demand-response actions. This proactive approach not only improves energy conservation but also enhances grid reliability and end-user satisfaction.

A key advantage of IoT-based energy systems is their capacity for adaptive control and scalability. As energy demands fluctuate in urban environments, IoT networks can dynamically adjust system parameters to respond to usage trends and external conditions, such as temperature, occupancy, or equipment failure. These capabilities are particularly valuable in smart city contexts where energy management must be integrated with other critical urban services. Beyond real-world implementation, simulation tools have played a vital role in evaluating and optimizing IoT-based energy systems before their physical deployment. One such tool is IoTNetSim, developed by Salama et al. (2019), which enables the simulation of complex IoT-based networks within urban energy environments. IoTNetSim allows researchers and practitioners to analyze various configurations of sensor placement, network topologies, energy consumption patterns, and data transmission behaviors. Through such simulations, stakeholders can test performance under diverse scenarios, assess trade-offs in design decisions, and identify potential bottlenecks or vulnerabilities within the system.

Simulation platforms like IoTNetSim are especially important in contexts where physical testing is impractical due to resource limitations or infrastructural constraints. They support experimentation with different communication protocols (e.g., ZigBee, LoRaWAN), node densities, and deployment strategies without the high costs and risks associated with live implementation. This is particularly relevant for developing regions, where simulation serves as a critical tool for planning scalable, low-cost, and context-aware energy monitoring systems. Overall, IoT-based energy monitoring represents a significant leap toward intelligent, data-driven energy management. By coupling physical devices with simulation-driven insights, these systems not only enhance operational efficiency but also contribute to the long-term sustainability and resilience of urban energy infrastructures.

2.3.2 Forecasting Techniques

Forecasting energy demand is a foundational component of effective energy planning, resource allocation, and grid stability, particularly in smart energy systems that must dynamically respond to fluctuating consumption patterns. Accurate and timely forecasting enables energy providers to anticipate peak demand, optimize generation and distribution, and implement responsive load-shedding or demand-response strategies when necessary. As energy consumption becomes increasingly complex—shaped by behavioral variability, weather patterns, socio-economic dynamics, and technological adoption—traditional linear regression models are proving inadequate in capturing the non-linear and seasonal nature of energy usage data. This has led to a surge in interest toward more robust, adaptable forecasting models that combine computational efficiency with interpretability. One such model is the Prophet forecasting algorithm developed by Taylor and Letham (2018). Prophet is a decomposable time series model that integrates trend, seasonality, and holiday effects in a manner that is both intuitive and statistically rigorous. It was specifically designed to balance performance with ease of implementation, making it accessible for both expert data scientists and practitioners with limited statistical training. A key strength of Prophet lies in its ability to handle missing data, outliers, and seasonal fluctuations with minimal need for data preprocessing. These features make it particularly well-suited for deployment in regions like Nigeria, where energy demand often follows cyclical patterns influenced by weather, agricultural cycles, or religious observances, and where complete or clean datasets may not always be available. By providing interpretable results and strong predictive performance even under imperfect data conditions, Prophet has become an increasingly popular tool for energy planners in developing countries.

In contrast, more sophisticated deep learning models such as Long Short-Term Memory (LSTM) neural networks have gained prominence for their ability to capture long-range dependencies and complex temporal dynamics within energy usage data. According to a review by Nikpour et al. (2023), LSTM models significantly outperform traditional statistical techniques in contexts where the data exhibit high degrees of non-linearity, behavioral noise, or missing values. LSTMs are particularly valuable in urban environments where user behavior may be unpredictable or influenced by diverse socio-economic factors. Their ability to "remember" long-term patterns and adjust dynamically to recent observations makes them ideal for modeling electricity consumption in heterogeneous and fast-changing settings. However, the complexity of LSTM models also means they require larger, well-structured datasets and substantial computational resources to be trained effectively. A comparative study by Talwariya et al. (2023) further examined the relative performance of Prophet and LSTM models in smart city contexts. Their findings suggest that the effectiveness of each model largely depends on the nature and quality of the data. Prophet was found to be more adaptable and robust in situations involving sparse or irregular datasets, where its built-in seasonality modeling and fault tolerance enabled reasonable forecasting accuracy with minimal parameter tuning. Conversely, LSTM models exhibited superior performance when trained on large, high-density datasets, particularly those reflecting fine-grained user behaviors or sub-hourly consumption metrics. These insights reinforce the idea that model selection should be driven by both the data environment and the operational objectives of the energy monitoring system. In summary, the evolution of forecasting techniques in smart energy systems illustrates a growing shift toward hybrid and context-sensitive modeling strategies. Whether opting for statistically grounded models like Prophet or leveraging the computational power of deep learning architectures like LSTM, the goal remains the same: to build energy systems that can anticipate demand with precision, adapt to uncertainty, and operate reliably across a wide range of infrastructural and behavioral conditions

2.3.3 Urban Energy Infrastructure in Developing Nations

Urban energy infrastructure in developing nations presents a complex interplay of opportunities and constraints, shaped by socio-economic realities, policy frameworks, and technological capacity. As urban populations grow rapidly across Africa, Asia, and parts of Latin America, energy demand is outpacing supply, placing unprecedented stress on aging and often inefficient grid systems. These infrastructural limitations hinder the seamless integration of smart energy technologies and pose significant barriers to the implementation of intelligent energy monitoring, forecasting, and distribution systems. A recent study by Ayodamola et al. (2024) provides a critical examination of Nigeria's national grid, highlighting severe inefficiencies in energy transmission and distribution. The study reports energy losses of up to 30%—primarily attributed to outdated infrastructure, unauthorized connections, poor maintenance practices, and lack of grid automation. Such losses not only undermine energy reliability but also inflate operational costs, reduce investor confidence, and perpetuate reliance on off-grid alternatives such as diesel generators and small-scale solar systems. These infrastructural weaknesses are symptomatic of broader systemic issues that affect many low- and middle-income countries, where national grids were originally designed for limited, centralized power generation and are now struggling to adapt to decentralized, demand-driven energy landscapes.

The deployment of Internet of Things (IoT) technologies in such environments is fraught with distinct challenges. One of the most significant obstacles is the inconsistent power supply, which undermines the reliability of sensor networks and communication devices that require uninterrupted power for data acquisition and transmission. Additionally, the high cost of IoT hardware—including sensors, gateways, edge processors, and communication modules—often exceeds the budgets of local governments and energy utilities operating under constrained financial conditions. Limited local manufacturing capacity and reliance on imported components further exacerbate these cost barriers, making large-scale implementation difficult without external funding or donor-supported interventions. Despite these challenges, innovative strategies are emerging to overcome deployment barriers and make smart energy solutions more viable in resource-constrained settings. Akara et al. (2025), for instance, advocate for simulation-first methodologies as a means of reducing cost and risk prior to physical deployment. In their approach, simulation tools are used to create virtual models of urban energy environments, enabling researchers and practitioners to test various IoT configurations, assess network performance, and evaluate system responsiveness under different scenarios. This not only helps validate the technical viability of proposed systems but also supports evidence-based planning and decision-making. Simulation-first strategies reduce the likelihood of costly implementation errors and help stakeholders identify the most efficient and context-appropriate technologies before committing to hardware investments.

Moreover, such methodologies align well with modular deployment strategies, where energy systems can be rolled out in phases—starting with high-priority zones or pilot areas—before being scaled to broader urban regions. This staged approach allows for gradual integration with existing infrastructure and provides valuable feedback loops that inform continuous improvement. In conclusion, while the development of urban energy infrastructure in developing nations is constrained by systemic inefficiencies, economic limitations, and technical barriers, the strategic application of simulation-based planning and modular deployment is creating new pathways for innovation. By combining data-driven modeling with pragmatic implementation strategies, developing regions can begin to bridge the technological gap and lay the groundwork for resilient, adaptive, and inclusive smart energy systems.

2.3.4 Existing Gaps

Despite the growing body of literature on IoT-enabled energy monitoring and forecasting systems, significant gaps remain—particularly in addressing the unique challenges and contextual dynamics of developing countries. Most existing studies and technological solutions are designed and validated within the context of high-income countries, where infrastructure is reliable, data availability is high, and system integration is relatively seamless. Consequently, simulation frameworks and predictive models are often benchmarked against well-structured environments with consistent power supply, robust communication networks, and standardized behavioral patterns—conditions that do not reflect the operational realities in many low- and middle-income nations. A critical deficiency in the current research landscape is the lack of localized simulation tools specifically tailored to the infrastructural and socio-behavioral contexts of developing nations. Existing simulation environments—such as iFogSim or IoTNetSim—though valuable for generic IoT evaluations, frequently assume stable connectivity, continuous sensor operation, and standardized power loads. These assumptions may not hold in regions like urban Nigeria, where irregular power supply, intermittent internet connectivity, and infrastructural degradation are common. As a result, the insights gained from such simulations may fail to translate effectively into real-world outcomes when deployed in these more volatile environments.

Furthermore, behavioral dynamics—a crucial element of energy consumption in urban households—remain largely underrepresented in existing energy prediction models. For example, urban Nigerian settings are characterized by irregular and adaptive patterns of energy use that diverge significantly from those observed in more structured societies. Households often operate in response to erratic blackout schedules, frequently switching between grid power, generators, and off-grid solar alternatives. Appliance usage tends to be sporadic and influenced by cultural, economic, and environmental factors such as religious observances, market days, or fuel scarcity. These localized consumption behaviors introduce high variability into energy demand patterns, which conventional models—especially those trained on uniform datasets—struggle to accommodate effectively. This disconnect between model assumptions and on-ground realities results in reduced forecasting accuracy, unreliable control automation, and ultimately, low adoption or failure of smart energy systems in developing contexts. Additionally, most existing research does not sufficiently account for data sparsity, sensor inaccuracy, or the high cost of frequent hardware replacement—all of which can severely impact the performance of IoT-based energy systems in resource-limited settings.

To address these issues, future research must prioritize the development of context-aware simulation platforms and behavioral models that accurately reflect the operational environments of developing nations. Such platforms should incorporate probabilistic models for power availability, simulate intermittent sensor behavior, and include modules to account for human factors such as adaptive appliance use and socio-economic constraints. Only through such localized and inclusive approaches can smart energy systems be effectively designed, tested, and deployed to meet the actual needs of communities in the Global South.

2.4 Proposed Contribution to Knowledge

This study aims to make substantial contributions to the growing field of smart energy systems, particularly within the context of developing nations such as Nigeria, by addressing both technological and contextual gaps identified in the existing literature. It introduces four key areas of contribution that collectively advance the state of research and practice in IoT-based energy monitoring, simulation, and forecasting. First, the study proposes the development of a localized simulation framework specifically tailored to the operational and infrastructural realities of Nigeria’s urban energy landscape. Unlike generic simulation tools benchmarked against idealized or Western-centric environments, this framework will incorporate Nigeria-specific grid characteristics, such as erratic power supply, blackout schedules, data sparsity, and the behavioral variability of urban households. The simulation environment will be constructed using a blend of real-world energy consumption data (where available) and synthetically generated data that reflects known patterns of power usage and outage behavior. This localized approach not only enhances realism and practical relevance but also provides a reusable and adaptable tool for researchers, planners, and policymakers working in similar data-constrained environments.

Second, the study introduces a dual-model forecasting engine that integrates and compares two widely recognized time series forecasting models: Facebook’s Prophet model and Long Short-Term Memory (LSTM) neural networks. While Prophet is known for its interpretability, seasonality modeling, and robustness to missing data, LSTM offers a deep learning approach capable of capturing complex temporal dependencies and non-linear consumption patterns. By applying both models to the same dataset and simulation environment, the study enables a comparative performance analysis that highlights the trade-offs between interpretability and predictive power. This comparative framework will inform model selection for different use cases, such as low-resource environments (favoring Prophet) versus high-data-density environments (favoring LSTM).

Third, this research contributes a scalable IoT system design blueprint grounded in modularity and contextual adaptability. The blueprint details the architectural design of a sensor-based energy monitoring system that can be incrementally implemented—starting from software simulations and eventually extending to hardware deployment in phases. Emphasis is placed on low-cost components, fault tolerance, and minimal dependency on continuous connectivity or power. This modular design approach is particularly useful for urban planners, utility providers, and policymakers seeking to roll out smart energy infrastructure in stages, based on budget, coverage area, and deployment readiness. Finally, the study offers a unique contribution through the transparent documentation of dataset assumptions and simulation parameters. One of the major critiques of existing research is the lack of clarity regarding the origin, structure, and assumptions embedded in the datasets used for model training and validation. This study addresses that limitation by explicitly disclosing the assumptions made in data generation, pre-processing, and simulation modeling. This transparency not only enhances the replicability of the research but also invites critical engagement from other researchers, allowing for refinement, adaptation, and collaborative expansion of the work. Collectively, these four contributions represent a holistic effort to bridge the gap between theoretical innovation and real-world applicability in smart energy research for developing countries. The study not only advances technical capabilities in simulation and forecasting but also promotes inclusivity, transparency, and scalability—principles essential for sustainable energy innovation in under-resourced urban contexts.