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Deep Learning Techniques in IoT-Enabled Smart Grids Review Approach for Energy Management

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ABSTRACT The increasing proliferation of smart grids and the growing share of renewable energy sources call for innovative and intelligent approaches to energy distribution management. Conventional energy management techniques encounter significant limitations, including suboptimal energy allocation, elevated operational expenses, and limited adaptability to dynamic load variations within the network. This study introduces an advanced smart grid architecture that incorporates IoT-based sensors and a control mechanism powered by deep learning algorithms. By leveraging data from IoT devices and centralized databases, the proposed system enables continuous monitoring of grid parameters, supports real-time analytics, and facilitates adaptive and predictive decision-making. These capabilities contribute to enhanced energy distribution efficiency, reduced technical losses, and improved overall system reliability. Furthermore, the architecture ensures robust resource allocation, even under conditions of unforeseen failures of energy assets, including generation units, distribution infrastructure, or end-users. The system also supports accurate demand forecasting and contributes to maintaining grid stability. Through the integration of IoT technologies, deep learning models, and real-time data processing, the proposed intelligent energy management framework is well equipped to address the challenges of increasing energy demand and the variability inherent in renewable energy generation.

KEYWORDS energy-efficient IoT solutions; deep learning; resource distribution management; network infrastructure optimization; real-time data analysis; environmentally sustainable energy management; Smart Grids.

I. INTRODUCTION

The rapid increase in global population and the growing deployment of renewable energy technologies are key factors driving the transformation of energy systems, necessitating advanced power management strategies [1]. Modern smart grids, enhanced by artificial intelligence (AI) and the Internet of Things (IoT), significantly contribute to efficient energy management by enabling automated control of energy flows, real-time monitoring, and data-driven decision-making, which collectively improve the utilization of available resources [2].

Recent advancements in IoT technologies have enhanced data acquisition, communication, and processing within smart grids, resulting in more accurate forecasting of energy consumption and more efficient energy distribution [3]. Nonetheless, conventional energy management techniques still pose serious limitations, such as inefficient power allocation, high operational expenditures, and poor adaptability to rapidly changing grid conditions [4].

To address these shortcomings, intelligent energy management systems incorporating deep learning methods are being actively explored. Such systems offer adaptive energy allocation, improved loss reduction, and increased grid resilience [5]. Powerful AI tools set for deep learning is particularly effective in analyzing vast datasets from diverse sources, offering novel solutions to complex energy system challenges [6]. Its application in smart grids enables enhanced analysis of consumption patterns, improved optimization of resource allocation, and higher reliability of overall grid performance [7].

The fusion of deep learning with IoT-based control frameworks allows for dynamic, real-time distribution of energy resources, contributing to waste reduction and improved operational efficiency [8]. However, this integration also introduces new challenges, including computational demands, scalability issues, and the need for robust network adaptability [9]. Addressing these challenges requires ongoing refinement of deep learning algorithms tailored for energy systems, with the goal of maximizing performance and efficiency [10].

In [11], a model proposed for forecasting the intra-hourly trends of electricity market imbalances in the Czech Republic, achieving a prediction accuracy of 81.8%. In [12], a global model developed to forecast imbalances in the Belgian energy system with a 15-minute resolution. The accuracy evaluation based on metrics such as the Winkler score and the Continuous Ranked Probability Score (CRPS). This model outperformed baseline (naive) approaches as well as commonly used algorithms like ARIMA and Quantile Regression Forests (QRF). Furthermore, Urdiales in [13] introduced a hybrid forecasting methodology for Belgian imbalance prediction, combining linear and nonlinear machine learning techniques to enhance modeling robustness.

In [14], an enhanced artificial intelligence (AI) with DL based approach proposed for predicting the signs of energy imbalances in the day-ahead electricity market. Additionally, in [15] presented a multi-step variant of the distributed lag autoregressive model for short-term forecasting of system imbalances. Their approach based on the assumption that the imbalance correlated not only with historical system measurements but also with forecasts of exogenous variables.

In the work [16], approaches to the optimal operation of cascade hydropower plants for forming the day-ahead electricity market schedule are presented. The authors apply mathematical optimization models considering hydrological, technical, and market constraints to improve water resource utilization efficiency and power system stability. The proposed optimization algorithms have strong potential for integration into IoT-enabled Smart Grid systems to enhance forecasting accuracy and automation in energy management processes.

In the work [17] an advanced Long Short-Term Memory (LSTM)-based approach is proposed for forecasting electricity imbalances in the Ukrainian power system. The authors conduct a comparative analysis of deep learning models to improve prediction accuracy and ensure grid stability under variable load and generation conditions. The research highlights the advantages of LSTM architectures in capturing nonlinear temporal dependencies, making them highly effective for real-time energy management within IoT-enabled Smart Grid environments.

In the paper [18] comprehensive optimization framework for off-grid hybrid renewable energy systems at Gaita Selassie, Ethiopia, is developed to achieve cost-effective and reliable electricity supply. The study integrates solar, wind, and battery storage technologies, using advanced optimization algorithms to balance system cost, reliability, and sustainability. The results demonstrate that such hybrid configurations can significantly enhance energy access and resilience, aligning with Smart Grid and IoT-based energy management strategies for decentralized power systems.

In paper [19] proposes an approach based on federated deep reinforcement learning (FDRL) for energy management in smart microgrids equipped with distributed resources (solar panels, batteries). Each local agent (in a home or building) is trained locally and then aggregates knowledge at the energy management system level to improve the solution across the entire microgrid. The primary goals are to reduce costs, reduce CO_2 emissions, increase autonomy, and protect user privacy. The study demonstrates that the federated approach enables efficient scalability while maintaining accuracy and reliability in IoT contexts.

This paper proposes a framework [20] that combines deep learning and IoT for real-time energy management. Specifically, the system includes short-term energy forecasting, communication between the energy manager and the consumer via IoT devices, and data preprocessing and normalization algorithms optimized for resource-constrained devices. The results demonstrate low prediction errors (MSE, RMSE) for both residential and commercial datasets, making the approach practical for Smart Grid/IoT environments.

In the work [21] proposes a framework for optimizing power distribution in smart grids with bidirectional dispatch (supply vs. demand) using data from IoT sensors. LSTM and MLP models are used to forecast demand and generation, as well as to adjust load and generation management in real time. The results demonstrate reduced load forecast errors, lower operating costs, and lower CO_2 emissions, especially during peak hours. This is a good example of how deep models and IoT can aid in grid management and balancing.

In the paper [22] proposes a comprehensive approach combining deep learning and graph neural networks for smart grid data analysis. The "GridOptiPredict" model includes three main components: load forecasting, state sensing, and resource allocation optimization. Experiments demonstrate high forecast accuracy, good sensitivity in network state detection, and efficient resource allocation. The paper demonstrates how the integration of various deep learning components can improve smart grid performance across various dimensions.

By leveraging real-time data and advanced machine learning models, deep learning-based platforms can provide accurate demand forecasts, support intelligent resource management, and stabilize smart grids under dynamic operating conditions [23]. These systems are capable of continuously learning and adapting to evolving energy consumption and production patterns, thereby maintaining grid balance and enhancing energy efficiency in real time [24].

This approach integrates the Internet of Things (IoT), real-time data analytics, and deep learning to effectively tackle the fundamental challenges associated with smart grid management, ultimately leading to the development of more adaptive, intelligent, and efficient energy distribution systems. The main goal paper is analyze possibilities of using smart grids based on the Internet of Things for intelligent energy management.

II. ARCHITECTURE SMART GRID WITH IOT ENABLED SENSOR AND DEVICES

In Fig. 1 shown structural model of energy resource distribution in a modern smart grid. This model combines edge computing, the Internet of Things (IoT), and deep learning algorithms.

In the proposed system, sensors and IoT devices constantly monitor and control many parameters of energy equipment. Key parameters include voltage, current, temperature, vibration, load, and the operational state of switches and transformers. Monitoring these factors enables early detection of irregularities and supports prompt action in case of faults or emergencies. In parallel, IoT sensors capture variations in the environment, shifts in demand, and real energy consumption. The resulting dataset provides valuable insights for deeper analysis and contributes to more efficient allocation of energy resources.

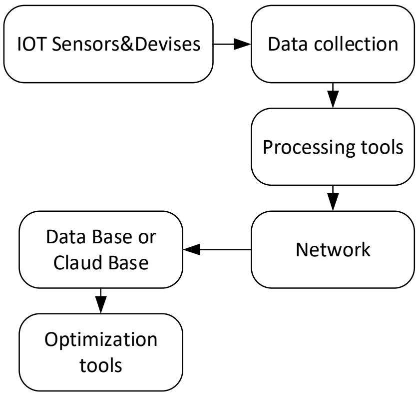

Figure 1. Smart Grid Architecture with IoT devices.

III. IOT AND DEEP LEARNING FOR SMART GRIDS SOLUTIONS

Smart grids that integrate deep learning, artificial intelligence, and the Internet of Things enable the most efficient use of resources and energy. As a result, they contribute to the development of more powerful and environmentally friendly energy sources that meet the requirements of sustainable development. Consider in detail the most used methods.

Energy-Net: A Deep Learning Model for Temporal Forecasting. The Energy-Net model introduces a deep learning framework tailored for forecasting temporal energy consumption. It incorporates spatio-temporal modules that utilize a Temporal Transformer (TT) to model temporal dependencies and a Spatial Transformer (ST) enhanced with convolutional layers and self-attention mechanisms to capture spatial features [25]. Validated on the IHPEC and ISO-NE datasets, Energy-Net demonstrates lower Root Mean Squared Error (RMSE) compared to existing models, while maintaining computational efficiency suitable for IoT environments in smart grids.

Energy Efficiency Optimization in Smart Grids via Machine Learning. This approach proposes a machine learning-based framework designed to enhance energy efficiency in smart grids. By analyzing residents' movement patterns and generating short-term consumption forecasts, the system aims to maximize the integration of renewable energy sources. It utilizes indoor localization technologies and smart meters to collect real-time data on user behavior and consumption, which is processed using an online machine learning model [26]. This enables dynamic optimization of solar energy distribution, reduces peak demand on central grids, and improves forecasting accuracy–achieved using limited computational resources.

Optimization of IoT-DRL-Based Smart Grids. This approach leverages resource management optimization in smart grids by integrating Deep Reinforcement Learning (DRL) within an Internet of Things (IoT) infrastructure [27]. The dynamic adaptability of DRL models to real-time changes in network conditions–including user behavior and sensor feedback–enables efficient energy utilization and waste reduction. This results in improved economic performance. A practical outcome of this method is a reduction in the number of energy units from 2700 to 2300 as the number of deployed IoT sensors increased from 100 to 500, highlighting enhanced throughput, resilience, and reliability of the smart grid system.

Energy Forecasting for Smart Buildings Using LSTM. This method applies a multi-level Long Short-Term Memory (LSTM) neural network within an IoT-based architecture to forecast and manage energy usage in smart buildings [28]. The LSTM model significantly outperforms traditional machine learning algorithms such as linear regression and random forests, achieving lower Mean Absolute Error (MAE) and RMSE. By enhancing prediction accuracy and operational efficiency, this approach contributes to cost savings, improved energy utilization, and more stable building energy systems.

Energy Optimization in Smart Cities Using Deep Learning This method focuses on reducing energy consumption in smart cities by applying deep learning techniques, particularly neural networks and recurrent neural networks (RNNs), within IoT-supported environments. Real-time data collected from sensors, devices, and smart grid infrastructures is analyzed to optimize energy usage, support operational decision-making, and improve device management. The resulting benefits include lower energy costs, reduced resource consumption, and decreased greenhouse gas emissions, contributing to sustainable urban development [29]. This solution is scalable and adaptable for implementation across different urban settings.

Energy Optimization in Hybrid Smart Grids. The proposed hybrid smart grid framework integrates multiple renewable energy sources–including photovoltaic, hydro, and thermal power–while supporting real-time energy expenditure optimization and cost recovery for urban environments [30]. The system incorporates a Flexible Operations Layer (FoL) to manage distribution and control functions efficiently. By promoting intelligent resource usage, the approach ensures reliable and sustainable energy delivery while improving the overall performance of hybrid smart grid infrastructures.

IoT-ML Integration for Enhanced Smart Grid Management. This approach explores the effective integration of Internet of Things (IoT), Machine Learning (ML), and Smart Grid (SG) technologies to optimize energy management in smart buildings. The system emphasizes remote monitoring and configuration of smart grid functions, enhancing occupant comfort and safety while reducing energy consumption [31]. By processing data from smart meters and IoT sensors, ML algorithms provide insights into consumption patterns and enable real-time optimization. The result is a more efficient, responsive, and intelligent smart grid infrastructure.

For effective energy management in the context of reasonable measures and places of integration of Internet of speech technologies (IoT), deep progress and predictive modeling from distributed systems, the most promising is the system with deep learning. The system continuously processes data in real time and adapts to optimize energy distribution, while maintaining reliability and cost-effectiveness. The solution will ensure a reduction in energy costs, increased operational efficiency and support for increased development.

IV. MATHEMATICAL FRAMEWORK FOR THE REALIZATION OF DEEP LEARNING FOR SMART GRIDS

The rapid evolution of intelligent energy grids has been significantly driven by the integration of advanced technologies such as the Internet of Things (IoT), edge computing, and deep learning. These innovations are transforming traditional energy systems by enabling more efficient management and real-time monitoring of energy resources. IoT devices, sensors, and smart meters collect vast amounts of data from energy networks, providing real-time insights into energy consumption patterns, grid performance, and potential issues. The integration of advanced technologies, such as IoT, edge computing, and deep learning, within intelligent energy grids requires a robust mathematical framework to optimize decision-making and data processing. One such framework that has gained traction in the management of energy systems is ORA-DL (Optimal Resource Allocation with Deep Learning). This framework combines optimization techniques with deep learning models to enhance the efficiency and adaptability of energy distribution networks, reducing latency and improving the responsiveness of the grid to changing conditions. In this study, the deep learning component is used primarily for forecasting key indicators from IoT-derived time-series data, and these forecasts are then integrated into the ORA-DL optimization-oriented decision framework.

The method of deep learning to ensure the optimal distribution of resources at reasonable measures with the vicinity of adaptive vagal coefficients $\left(l_g f\right)$ and the formation of demand $\left(\left[a-jw''\right]\right)$ the optimal distribution of energy $Ka\left[w-uq''\right]$ in intellectual measures $Ja\left[w-ue''\right]$ can be representations to get relatives by next eq.:

$$l_g f\left[a-jw''\right]:\to Ka\left[w-uq''\right]+Ja\left[w-ue''\right]. \quad (1)$$

To promote the efficiency of resource utilization, smart power is connected to the Internet of Things (IoT) by adopting solutions based on deep knowledge. Maximize the distribution of energy in intellectual measures $\left[w-iuw''\right]$:

$$P_a w:\to Xa\left[w-uq''\right]+\left[w-iuw''\right]-Va\left[ew-uq''\right]. \quad (2)$$

Eq. (2) describes the adaptive distribution of tension $P_a w$ with the help of predictive $Va\left[ew-uq''\right]$ modifiers of pain $Xa\left[w-uq''\right]$ and systemic pain. Level 2 guarantees that the measure is stable and results in intelligent decision making with low energy consumption. The result $Va\,w''$ of the integration of system characteristics $\left[w-uq''\right]$ and voltage adjustment $Ca:\to A$ to optimize the level of adaptive output $Ba\left[w-uq''\right]$ allows optimizing the energy distribution:

$$Ca:\to A\left[w-uq''\right]+Ba\left[w-uq''\right]*Vaw''. \quad (3)$$

By preserving electrical stability and energy efficiency, the system guarantees an economically efficient distribution of resources. With the understanding that commercial and industrial enterprises can increase their energy savings through energy management systems, charging electric vehicles and saving energy. Residents will benefit from the availability of intelligent healthcare providers, energy storage, and home displays that allow for more efficient energy management. The core system combines energy management with additional advanced infrastructure, further development of monitoring and automation, ensuring increased distribution of hybrid energy, stabilization boundaries and rational energy utilization. This will make it possible to achieve a more reliable and environmentally friendly environment

$$Z_a e\left[a-uw''\right]:\to Ls\left[fi-ane''\right]*Ka'\left[s-fw''\right]. \quad (4)$$

stability of the operating voltage $\left[a-uw''\right]$ of the system $\left(Ka'\left[s-fw''\right]\right)$ and dynamically adjusted parameters ($Ls\left[fi-ane''\right]$) to predict the coefficient of adaptive vicoristic energy $\left(Z_a e\right)$. This ensures improved resource management, less inefficiency and greater energy efficiency

$$f_c s\left[ao-sm''\right]:\to Ja\left[c-dj''\right]*Ka\left[s-uw''\right]. \quad (5)$$

The function $\left(f_c s\right)$, which optimizes the performance of the intelligent network $Ja\left[c-dj''\right]$ based on $Ka\left[s-uw''\right]$ scaling adaptation, changes the system adjustment $\left(\left[ao-sm''\right]\right)$, as shown in line (5). Due to the flexible flexibility of the circuit, level 5 guarantees an effective distribution of energy with minimal operating inputs and outputs

$$M_x s\left[ak-sm''\right]:\to dhd\left[c-tw''\right]+Va\left[s-uw''\right]. \quad (6)$$

Adaptive power modulation $\left(M_x s\right)$ is optimized for the distribution of power resources $Va\left[s-uw''\right]$ by eq. (6) by enabling dynamic water control $\left(\left[ak-sm''\right]\right)$ and frequency regulation $\left(dhd\left[c-tw''\right]\right)$. Therefore, minimizing wasted energy and increasing the stability of the flow, the system guarantees efficient energy consumption.

V. EXPERIMENTAL VALIDATION

The study of the feasibility of the deep learning method based on the selected framework was made for hourly data on balancing energy volumes (up and down). The history consists 8704 points. The test period is 21 days. Studies were performed with a forecast horizon of 72 points (7 by 72) and 504 points. RMSE was selected as the primary metric due to its interpretability in the original units and common use in forecasting; additional metrics and baseline models (e.g., MAE, R^2, ARIMA, linear regression) will be included in an extended evaluation. Moreover, according to the obtained RMSE values (for down and up samples) and RMSE (for up sample), in a third of the cases, the values of the ensemble forecast errors are lower than the real data. Preliminary, the accuracy of the forecast of demand volumes for balancing resources is considered sufficient to use the obtained forecasting results in the procedures for situational planning of additional supply of services for loading and unloading from hydroelectric units. So in this case considering that, statistical indicators for price time series from the point of view are more stable. The presented experimental validation is intended as a feasibility study on real hourly balancing-energy time series; broader cross-period and multi-baseline experiments are planned as future work.

In Fig. 2 and Fig. 3 show random day graphs (30 history point) for this day price time series in the upward (loading) and downward (unloading) directions, respectively.

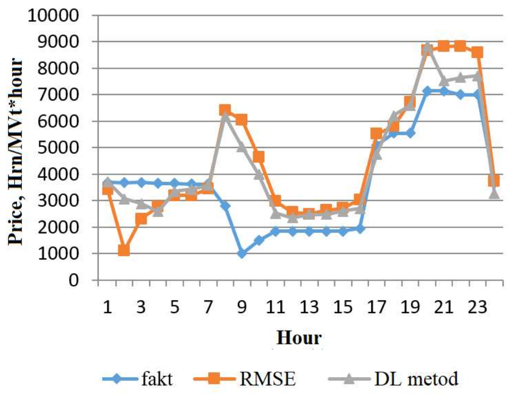

Figure 2. Example of forecasting time series of prices for loading and unloading respectively.

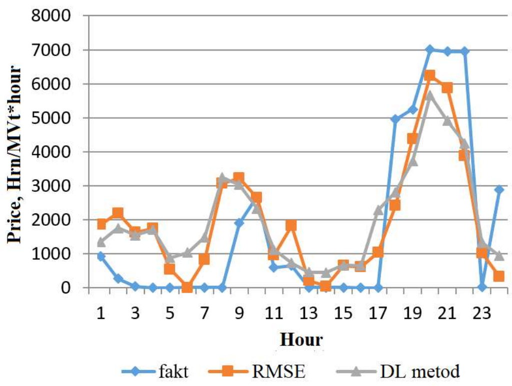

Figure 3. Example of forecasting time series of unloading prices.

Several experiments with different forecasting horizons and history volumes were conducted when forecasting using the mathematical framework for the realization of deep learning for smart grids. The model demonstrated an advantage over moving averages in the accuracy of reproducing actual data. However, both models turned out to be quite inaccurate, especially in the case of forecasting prices for unloading services, where the root-mean-square error reached high values.

The conducted experiments demonstrate that the deep learning framework, when applied to balancing energy volumes with horizons of up to 504 points, achieves forecast accuracy sufficient for preliminary integration into situational planning of hydroelectric unit loading and unloading. Despite some variations in RMSE across up and down samples, in nearly one-third of the cases, ensemble forecast errors were lower than deviations observed in real operational data. This indicates that the use of data-driven forecasting tools is promising for supporting market mechanisms and short-term operational decision-making. Moreover, the obtained results confirm that statistical properties of price time series in balancing markets remain relatively stable, which further strengthens the potential for embedding advanced predictive models into real-world grid management processes.

Nevertheless, moving from isolated forecasting experiments toward holistic smart grid management reveals deeper challenges. Current infrastructures still face limitations in resource allocation efficiency, difficulties in maintaining stability under fluctuating demand, and risks of excessive or uncoordinated energy usage. These issues highlight the need for systems that go beyond simple prediction and instead enable proactive optimization and adaptive control.

In this context, improving the automation and optimization of energy distribution requires the combined use of energy-efficient Internet of Things technologies and deep learning models. Their integration has already begun to reshape the way smart grids respond to dynamic demand–supply conditions, creating opportunities for more resilient and sustainable energy ecosystems. However, without targeted mechanisms, the benefits of such integration are constrained by persistent inefficiencies, such as suboptimal allocation of balancing resources and energy losses during peak load conditions.

To address these challenges, we introduce ORA-DL, a novel deep learning–based system that not only improves demand forecasting but also leverages predictive insights to optimize resource distribution across the grid. ORA-DL enhances situational awareness by integrating multi-source IoT data, enables adaptive allocation of balancing resources, and contributes to overall grid stability even under uncertain demand conditions. Unlike traditional forecasting tools, ORA-DL incorporates optimization-oriented feedback loops, allowing it to bridge the gap between accurate prediction and sustainable decision-making. In addition, the system is designed with scalability and robustness in mind, making it suitable for integration into large-scale energy infrastructures and adaptable to future changes in consumption patterns and renewable generation dynamics.

As a result, ORA-DL provides a comprehensive foundation for future energy management systems, aligning predictive analytics with environmentally responsible smart grid operations. By combining advanced forecasting, intelligent optimization, and sustainable management strategies, it addresses the shortcomings of existing solutions and creates a pathway toward more efficient, stable, and resilient energy networks.

VI. DISCUSSION

The experimental and analytical results obtained in this study confirm the effectiveness of integrating deep learning techniques with IoT-enabled architectures for intelligent energy management in smart grids. The findings highlight that the proposed ORA-DL framework not only enhances the accuracy of energy demand forecasting but also contributes to adaptive and optimized resource distribution across complex energy networks. Compared with traditional methods such as moving averages or linear regression models, the deep learning approach demonstrated higher predictive stability and adaptability to dynamic grid conditions, particularly when managing balancing energy volumes in hydroelectric systems. A broader quantitative benchmark against classical and ML baselines (e.g., ARIMA and linear regression) is an important next step and is planned for an extended version of the study.

The results also indicate that the integration of IoT sensors and real-time analytics allows for continuous monitoring of key grid parameters, improving situational awareness and enabling proactive decision-making. These capabilities are essential in addressing fluctuations in renewable generation and variable consumer demand, which are major challenges for modern power systems. The observed improvements in Root Mean Squared Error (RMSE) values across forecasting horizons up to 504 points suggest that the system can reliably support short-term operational planning and market balancing processes.

Despite these advances, the study also reveals persistent limitations. Forecasting accuracy decreases when predicting price trends for unloading operations, suggesting that the current model may be sensitive to noise or abrupt market fluctuations. Moreover, while the proposed ORA-DL framework effectively integrates forecasting and optimization, its computational complexity could present challenges for deployment in resource-constrained IoT environments. Key limitations include sensitivity to abrupt fluctuations for certain series and potential computational overhead for deployment on resource-constrained IoT/edge devices. Therefore, further research is required to enhance algorithmic efficiency and scalability, particularly for large-scale distributed energy systems.

From a practical perspective, the implementation of ORA-DL in real-world infrastructures – such as the Integrated Energy System of Ukraine – could significantly improve demand forecasting accuracy, facilitate better balancing of generation and consumption, and reduce technical losses. This is especially relevant in contexts where the integration of renewable energy sources introduces higher variability and uncertainty. By coupling deep learning models with IoT-enabled monitoring, operators can achieve more flexible and sustainable management of energy assets.

The comparative analysis with related works demonstrates that the proposed approach aligns with global trends in AI-driven energy systems. Similar architectures – such as Energy-Net [25] and federated DRL-based management systems [19] – also report improved prediction and optimization outcomes, confirming that deep learning represents a transformative direction in smart grid evolution. However, unlike most existing approaches focused solely on forecasting, ORA-DL incorporates feedback-based optimization loops, bridging the gap between prediction and control.

Overall, the discussion emphasizes that while the combination of IoT and deep learning offers clear benefits for intelligent energy management, success depends on addressing challenges of scalability, interoperability, and cybersecurity. Future efforts should focus on hybrid architectures that combine deep learning with reinforcement learning for adaptive control, edge computing for latency reduction, and privacy-preserving mechanisms for distributed data processing. By doing so, next-generation smart grids can evolve toward self-organizing, resilient, and environmentally responsible energy ecosystems.

VII. CONCLUSIONS

This paper has presented a comprehensive framework for IoT-enabled smart grids that integrates deep learning methods with energy optimization strategies. The use of data from IoT devices and sensors in real-time analytics and predictive modeling significantly enhances the automation of grid operations, improves the efficiency of resource utilization, and strengthens grid stability. The conducted experiments with balancing energy volumes demonstrated that deep learning–based forecasting achieves sufficient accuracy for preliminary integration into situational planning, particularly in the management of hydroelectric unit loading and unloading. These findings emphasize the practical potential of advanced forecasting tools to support short-term operational decisions and market mechanisms.

The proposed ORA-DL system extends beyond isolated prediction tasks by incorporating optimization-oriented feedback loops and adaptive allocation mechanisms. Through the integration of multi-source IoT data, ORA-DL enhances situational awareness, optimizes balancing resource distribution, and contributes to maintaining grid stability under uncertain and fluctuating demand conditions. This holistic approach not only addresses existing challenges, such as inefficient resource allocation and excessive energy consumption, but also provides a scalable and robust platform for sustainable energy management. The optimization aspect is represented in the proposed feedback-based allocation mechanism; an explicit optimization/convergence curve will be provided in future extended work.

In the context of the Integrated Energy System of Ukraine, improving forecasting accuracy and more precise accounting of consumption are of particular importance. Enhancing these aspects is essential for ensuring the effective operation of electricity market participants and for maintaining the overall sustainability, flexibility, and reliability of the energy system. Furthermore, the implementation of intelligent forecasting and optimization tools contributes to achieving environmental objectives by reducing unnecessary energy usage and supporting the integration of renewable energy sources.

Nevertheless, further research is required to refine the proposed approaches, ensuring their robustness, scalability, and long-term effectiveness under diverse operating conditions. Future work should focus on expanding the system to include reinforcement learning–based control mechanisms, incorporating advanced market-driven optimization models, and testing the framework under scenarios with high penetration of distributed and renewable generation. In this way, the presented concepts lay the groundwork for next-generation smart grids that are adaptive, resilient, and capable of meeting the increasing demands of modern energy systems.

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