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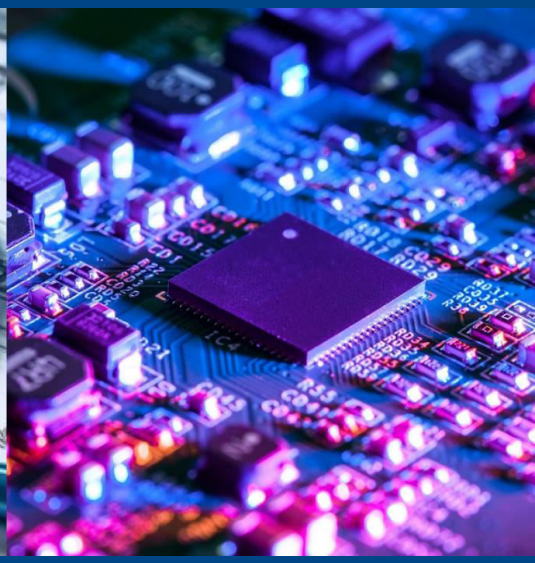

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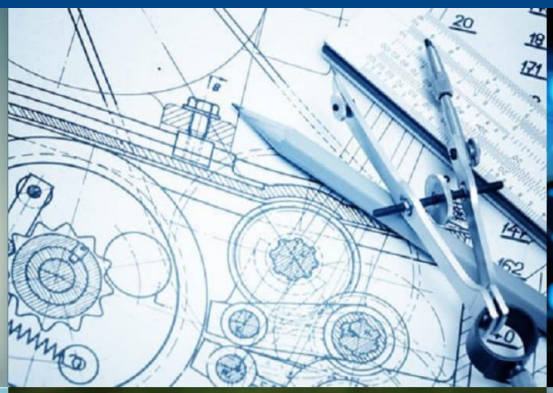

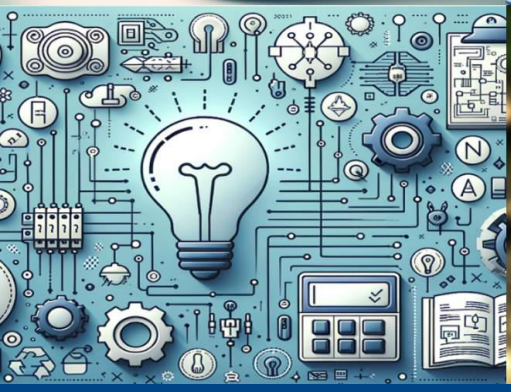

Impact Factor: 9.864 **Volume 9, Issue 9, September 2026**

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International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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GIS-Based Watershed Delineation and Terrain Analysis of the Krishna River Basin using DEM and QGIS

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ABSTRACT: Watershed delineation is an important step in hydrological assessment, water-resource planning and terrain-based analysis. This study presents a GIS-based workflow for delineating and characterizing sub-watersheds of the Krishna River Basin using a Digital Elevation Model (DEM) and QGIS. The workflow includes DEM clipping and preprocessing, flow-direction and flow-accumulation analysis, drainage-network extraction, sub-watershed delineation, contour generation and slope analysis. Area and perimeter were extracted from the resulting sub-watershed polygons. Seven mapped units cover a combined area of 49,658.72 km². The results demonstrate the usefulness of DEM-based QGIS processing for systematic watershed characterization and provide a spatial basis for subsequent hydrological and watershed-management studies.

KEYWORDS: Watershed delineation; DEM; QGIS; Flow direction; Flow accumulation; Sub-watershed; Terrain analysis

I. INTRODUCTION

Watersheds provide a practical spatial framework for understanding the movement and concentration of surface runoff. Digital elevation models allow terrain-controlled drainage patterns to be represented as raster surfaces, from which flow direction, accumulated flow and drainage networks can be derived. GIS-based watershed delineation reduces the need for manual interpretation of topographic maps and provides reproducible spatial outputs for hydrological analysis. The present study applies a QGIS-based DEM workflow to the Krishna River Basin with emphasis on sub-watershed delineation, drainage representation, contour generation, slope mapping and geometric characterization using area and perimeter.

II. LITERATURE SURVEY

Previous studies established the use of digital elevation data and raster algorithms for automated drainage extraction and watershed delineation. O'Callaghan and Mark demonstrated an automated approach for extracting drainage networks from digital elevation models, while Jenson and Domingue described DEM-based procedures for watershed and drainage-basin analysis. Tarboton later developed an efficient method for determining flow directions and upslope areas. These developments form the methodological basis for modern GIS hydrological workflows. The present work applies these concepts in an integrated QGIS environment to produce spatially explicit watershed and terrain outputs.

III. STUDY AREA

The study focuses on the Krishna River Basin represented in the prepared GIS project. The processed DEM shows an elevation range approximately from 510 m to 1,427 m in the displayed raster legend. The basin contains varied terrain, with relatively stronger relief visible in the western and north-western portions and comparatively gentler terrain toward the eastern portion. Seven mapped sub-watershed units were identified in the supplied attribute table: Verna, Panchaganga, Koyana, Krishna_Bhima, Dhudhaganga, Malaprabha and Ghatprabha.

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IV. DATA AND METHODOLOGY

The principal input was a Digital Elevation Model prepared and clipped to the Krishna River Basin study extent. All hydrological processing and cartographic outputs were produced in QGIS. The supplied project outputs include the clipped DEM, flow-direction raster, flow-accumulation raster, drainage/stream network, contour maps, 100 m contour map, slope map and sub-watershed delineation. Area and perimeter values were obtained from the watershed attribute table supplied with the project.

The workflow was implemented sequentially. First, the DEM was clipped to the study extent and preprocessed to remove depressions/sinks. Second, flow direction was calculated to represent the direction of downslope surface-water movement. Third, flow accumulation was derived to identify cells receiving contributions from upslope areas. High-accumulation pathways were used to represent the drainage/stream network. These drainage patterns were then used to delineate sub-watershed units. Finally, contours at the selected interval and a slope raster were generated from the DEM, while area and perimeter were calculated for the delineated polygons.

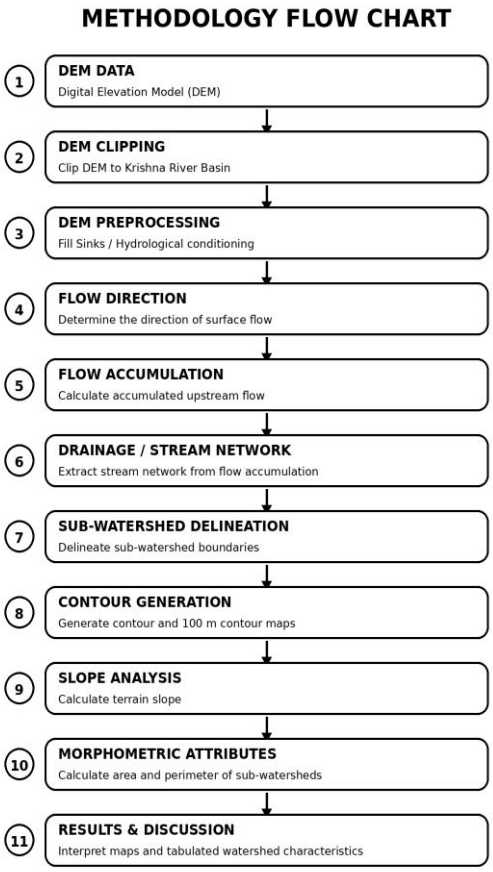

Fig.1.QGIS-based workflow adopted for DEM processing, drainage extraction and sub-watershed delineation.

The workflow summarizes the complete GIS sequence used in the study, beginning with DEM preparation and sink removal and continuing through flow analysis, drainage extraction and sub-watershed delineation. The steps are performed sequentially so that each hydrological output supports the next stage of analysis.

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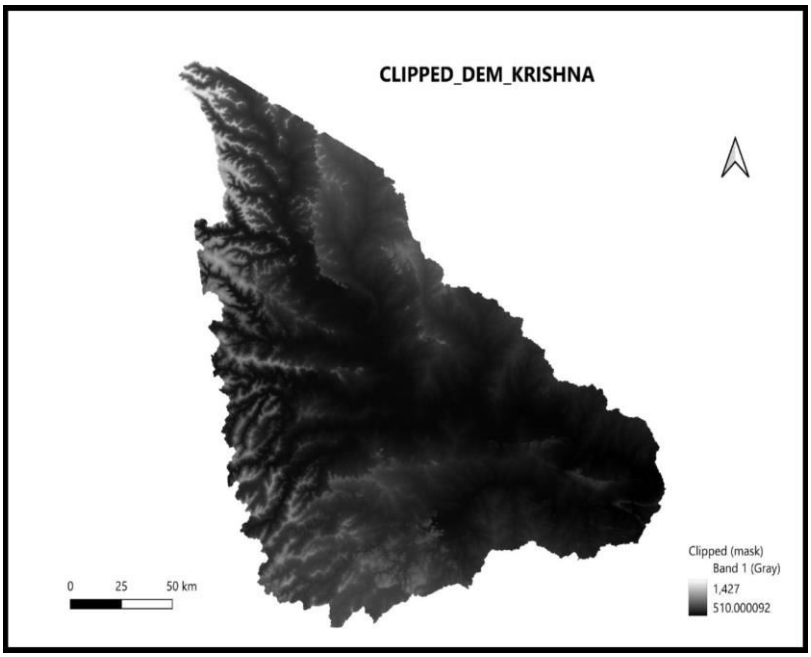

Figure.1. Clipped Digital Elevation Model (DEM) of the Krishna River Basin.

The clipped DEM represents the elevation surface used as the primary terrain input for hydrological processing. It provides the basis for identifying surface flow patterns and subsequent watershed delineation.

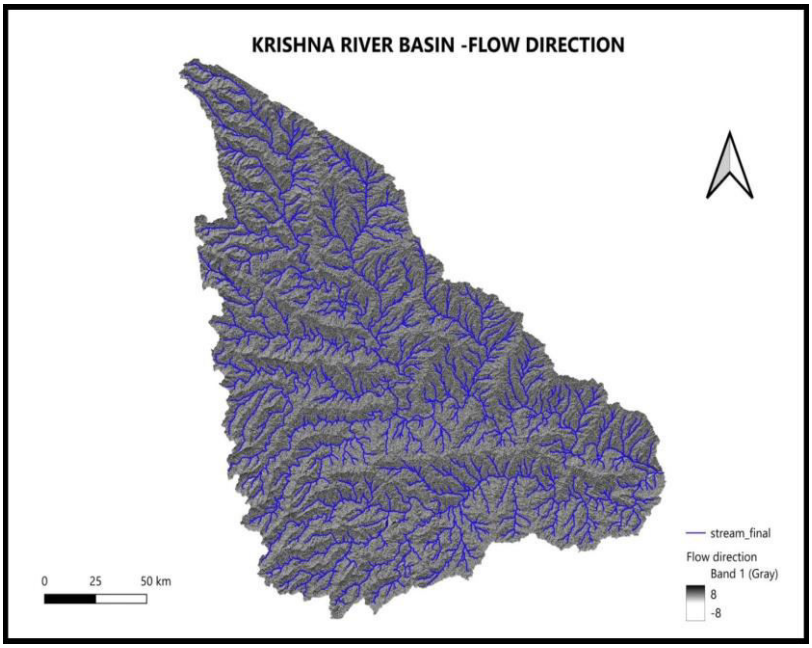

Figure.2.Flow Direction map of the Krishna River Basin

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The flow-direction raster assigns a downslope flow direction to each DEM cell. This output establishes the direction in which surface water is expected to move across the terrain.

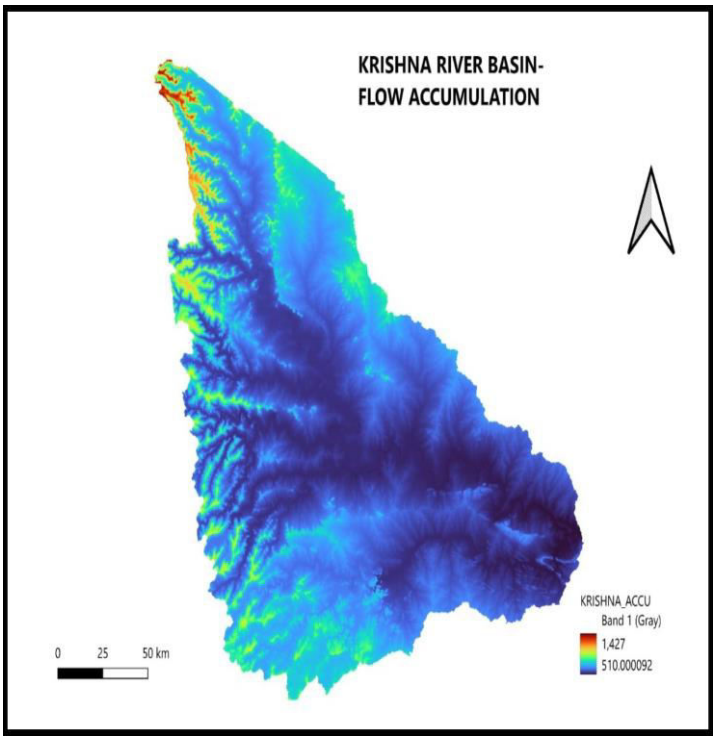

Figure.3.Flow Accumulation map of the Krishna River Basin

The flow-accumulation map highlights cells receiving runoff from upstream areas. Higher accumulation values help identify concentrated drainage paths and support extraction of the stream network.

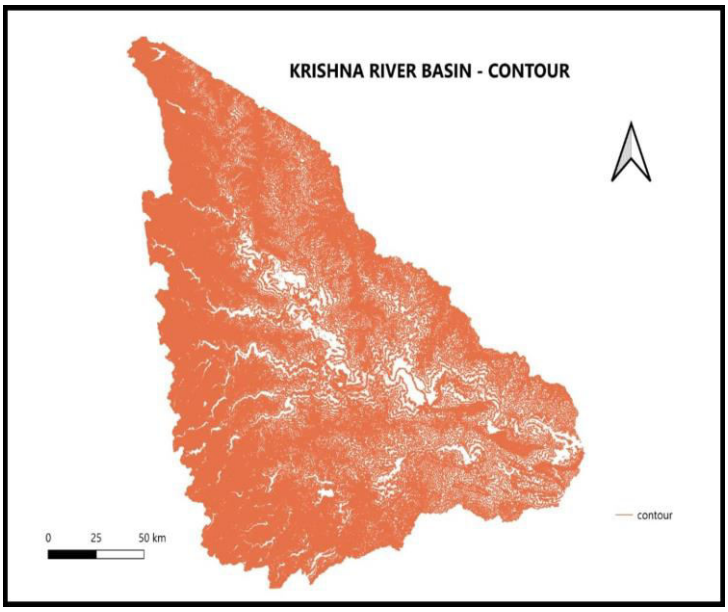

Figure.4.Contour map of the Krishna River Basin

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The contour map represents lines joining locations of equal elevation. It helps visualize terrain relief, slope characteristics and the general topographic pattern of the study area.

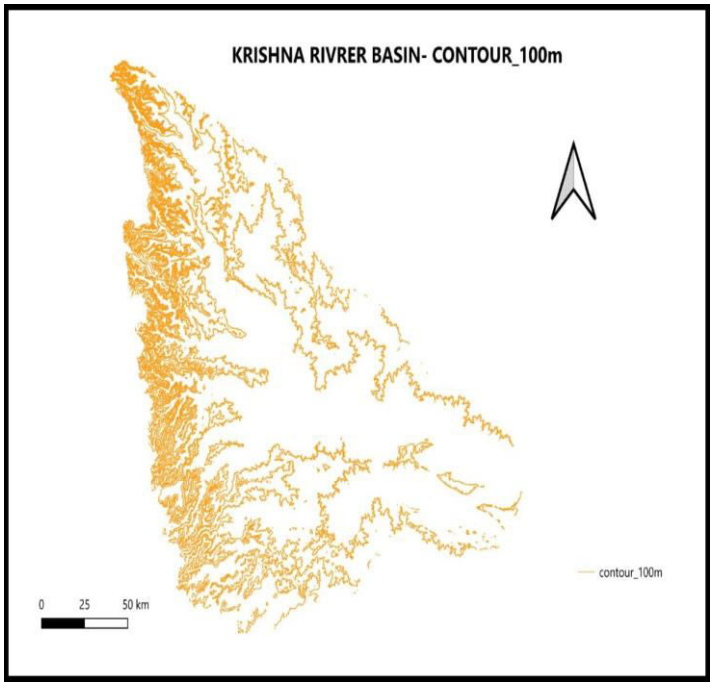

Figure.5.100 m Contour map of the Krishna River Basin

The 100 m contour interval provides a simplified representation of major elevation changes over the basin. It is useful for interpreting broad terrain variation and elevation zones.

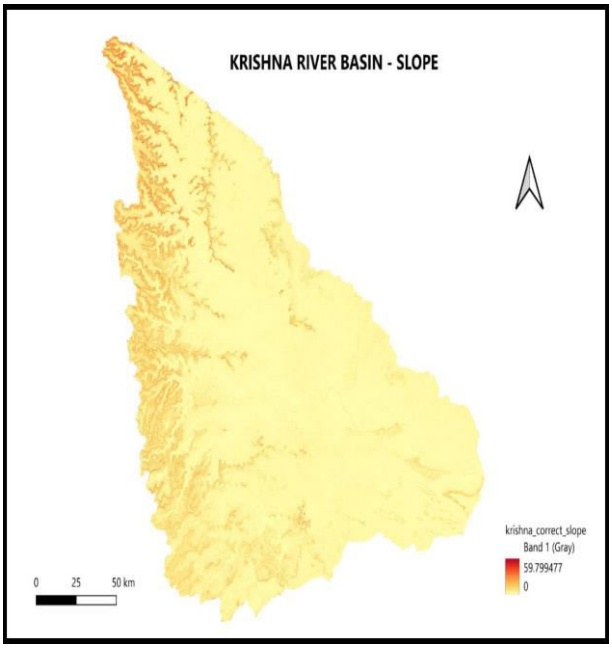

Figure.6.Slope map of the Krishna River Basin

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The slope map shows the spatial variation of terrain steepness derived from the DEM. It helps distinguish relatively gentle areas from steeper terrain that may influence runoff concentration.

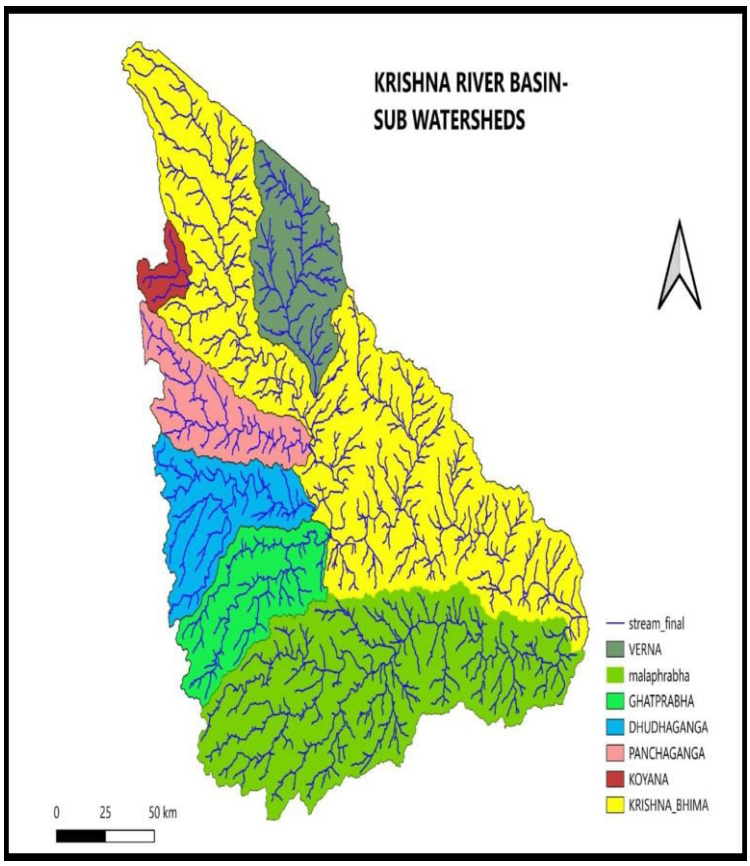

Figure.7. Sub-watershed delineation and drainage network of the Krishna River Basin.

The final delineation partitions the mapped basin into seven sub-watershed units and displays the associated drainage network. The result provides a spatial framework for area, perimeter and further hydrological analysis.

V. RESULTS AND DISCUSSION

The GIS outputs show a coherent drainage pattern across the study area. The flow-direction and flow-accumulation products provide the hydrological basis for stream-network extraction, while the sub-watershed map partitions the study region into seven named units. The supplied attribute table reports a combined mapped area of 49,658.72 km² (sum of the seven units; the displayed table rounds this to 49,658.71 km²). Among the mapped units, Krishna_Bhima accounts for 31,713.61 km², followed by Malaprabha at 8,635.38 km². Koyana is the smallest mapped unit at 427.32 km². Contour and slope outputs provide additional information on relief and terrain gradients that can support subsequent runoff, erosion and watershed-management studies. Because this study is based on the supplied GIS project outputs, the numerical results should be interpreted within the spatial extent and processing settings used in that project.

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Table I. Area and Perimeter of Delineated Sub-Watersheds

Sub-watershed	Area (km²)	Perimeter (km)	Area (%)
VERNA	2,010.78	315.52	4.05
PANCHAGANGA	2,032.93	409.96	4.09
KOYANA	427.32	167.78	0.86
KRISHNA_BHIMA	31,713.61	1,531.23	63.86
DHUDHAGANGA	2,380.71	430.96	4.79
malaprabha	8,635.38	739.84	17.39
GHATPRABHA	2,457.99	396.50	4.95
Total mapped units	49,658.72	3,991.79	100.00

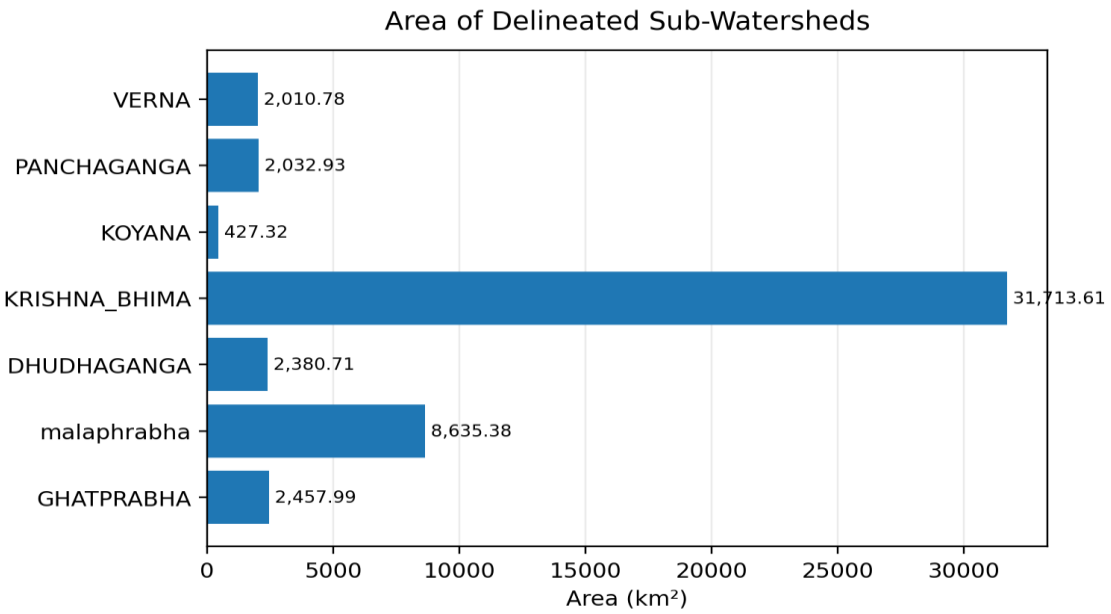

Fig.8.Area distribution of the delineated sub-watersheds

The chart compares the mapped area contribution of the seven delineated units. Krishna_Bhima forms the largest mapped unit, while Koyana represents the smallest among the listed sub-watersheds.

The supplied attribute table contains seven named sub-watershed units. The sum of the displayed area values is 49,658.72 km²; the source screenshot displays 49,658.71 km² after rounding. The table above retains the individual values supplied by the project and calculates the area percentages from their sum. These geometric descriptors provide a basis for comparing the spatial extent of the delineated units.

VI. CONCLUSION

A DEM-based QGIS workflow was successfully organized for watershed delineation and terrain characterization of the Krishna River Basin. The sequence from DEM preprocessing through flow direction, flow accumulation, drainage-network extraction and sub-watershed delineation produced spatially interpretable outputs. Contour and slope maps complemented the hydrological analysis, while area and perimeter measurements quantified the mapped sub-watershed

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units. The resulting GIS database and maps can serve as a foundation for more detailed hydrological modelling, morphometric analysis, runoff estimation, erosion assessment and watershed-management planning.

VII. FUTURE SCOPE

Future work may extend the analysis to morphometric parameters such as drainage density, stream frequency, bifurcation ratio, relief ratio and form factor. Integration with rainfall, soil, land-use/land-cover and runoff observations can support hydrological modelling and watershed-prioritization studies. Field validation of the extracted drainage network and comparison with authoritative hydrographic datasets would further strengthen the analysis.

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ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Intelligent Industrial Building Energy Management Using Hybrid LSTM–PPO Learning

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ABSTRACT: This study explores the implementation of an intelligent energy management system for industrial buildings, leveraging the capabilities of artificial intelligence (AI) technologies. The approach integrates advanced data analytics, machine learning algorithms, and real-time monitoring to optimize energy consumption, enhance operational efficiency, and reduce costs. Key components include the deployment of sensors, implementation of AI-driven optimization algorithms for dynamic control of energy-consuming systems. The system also incorporates demand response strategies, automated control systems, and continuous learning mechanisms to adapt to changing conditions and user behavior. User engagement interfaces are designed to promote energy-efficient practices, and integration with renewable energy sources enhances sustainability. The study highlights the potential for significant cost savings, reduced environmental impact, and improved regulatory compliance through the intelligent management of industrial building energy based on AI technologies. To enhance the efficiency of energy-saving practices in industrial buildings by integrating artificial intelligence technology. This integration is used to analyze and manage the intelligent energy-saving systems in these buildings, ultimately leading to a reduction in energy consumption. The paper delves into the circuit structure, workflow, and functionality of energy-saving systems, explaining how they control electrical equipment and the specific hardware components involved. The paper also employs collected data to create a predictive model for energy consumption. Finally, an intelligent management system for conserving energy in industrial buildings is developed, considering various constraints and optimization criteria. The study's data analysis results indicate that this artificial intelligence-based energy-saving system is effective and has a significant impact on the overall energy management of industrial buildings.

KEYWORDS: Artificial Intelligence; Industrial Building Energy Management; LSTM; Proximal Policy Optimization; Energy Optimization

I. INTRODUCTION

The industrial sector plays a pivotal role in global economic activities, but its energy consumption often constitutes a substantial portion of overall operational costs and environmental impact. As the world faces increasing energy challenges and environmental concerns, there is a growing imperative to optimize energy usage in industrial buildings. Traditional energy management approaches fall short in dynamically adapting to the complex and evolving nature of industrial processes [1]. In response, this study introduces an intelligent energy management system grounded in artificial intelligence (AI) to revolutionize how energy is consumed, monitored, and controlled within industrial facilities. The integration of AI technologies aims to enhance the efficiency of industrial building operations by making data-driven decisions, predicting energy consumption patterns, and optimizing energy usage in real time. This approach goes beyond static, rule-based systems, offering a dynamic and adaptive framework capable of responding to changing conditions and user behaviors [2]. By leveraging advanced data analytics, machine learning algorithms, and automation, the system seeks to achieve not only significant cost savings but also a reduction in the environmental footprint associated with industrial energy consumption. This introduction provides an overview of the key components of the proposed intelligent energy management system, including data collection through sensors and IoT devices, predictive modeling for forecasting, and AI-driven optimization algorithms. The study also explores the integration of demand response strategies, automated control systems, and continuous learning mechanisms, along with user engagement interfaces. Additionally, the incorporation of renewable energy sources is examined to promote sustainability in industrial operations. The collective impact of these components is anticipated to result in a more resilient, cost-effective, and environmentally friendly approach to managing energy in industrial buildings. As industries navigate a rapidly changing

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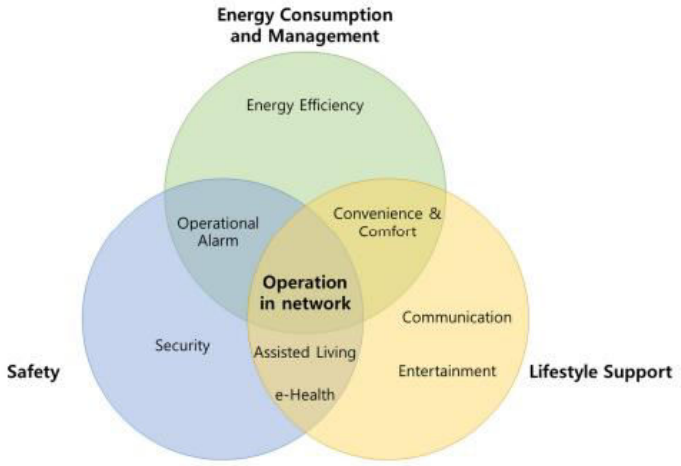
energy landscape, the application of AI in energy management stands out as a promising avenue for achieving a harmonious balance between economic viability and environmental responsibility [3].

Intelligent management of industrial building energy saving based on artificial intelligence (AI) involves the application of advanced technologies to optimize energy consumption, enhance efficiency, and reduce costs in industrial facilities. This approach typically utilizes AI algorithms, machine learning techniques, and data analytics to make data-driven decisions and control systems that govern energy usage [4].



Urban systems consist of numerous multi-level dynamic units that serve as integral features in the organization of societies. These units govern the smooth running of society and the control of political frameworks, and they also play essential roles in many aspects of the urban form. Flexibility, efficiency, and sustainability are required in the technological structures that are responsible for the smooth operation of the interconnected units in the urban environment. As the global population grows and the pace of urbanization continues unabated, the construction of smart cities with large commercial and residential buildings is expected to accelerate [5]. Information and communication technologies and the Internet of Things (IoT) methodologies are central to the creation of smart cities. The implementation of these technologies in modern cities is driving the transition from the twentieth-century concept of cities to the smart cities of the future.

A key observation here is that while alternatives may be found for many aspects of traditional city living, there is no substitute for energy or power from sources, as the whole edifice of modern life is built upon it. Energy is absolutely indispensable in the smooth-running of essential urban elements [6]. The impact of the specific type of energy sources, their availability, and their pattern of utilization is considerable in the urban environment. To maintain stability and efficiently drive the collective intelligent infrastructure of smart cities, a stable urban energy system that utilizes a smart technological framework must be established. It is expected that considerable energy savings will be a feature of these more productive, more comfortable, and more sustainable cities of the future [7]. The efficiency and reliability of communication systems, transportation networks, sewage and water systems, production and the service industry, buildings, and the utilities in the human habitat depend on an efficient and intelligent urban energy structure.

Significant advances in computer and communication technologies in recent years have led to the use of AI in urban energy transitions. Intelligent control enabled by the utilization of computer simulations has automated the management of energy in a variety of urban environments. The rapidly expanding role of AI in urban planning is largely due to its wide-ranging potential and its ability to sustain autonomous operations [8]. While many in the general public still tend to consider AI a far-fetched idea that belongs to the realm of science fiction, AI-systems have already become a reality in the modern infrastructure. Recent developments in AI have led to progress in solving the urban aspects of impulsiveness, uncertainty, mismatch, complexity, and the discrepancies of evolution. AI technologies have given us automated tools to design, analyze, simulate, control, diagnose, and supply reliable energy within urban neighborhoods. These tools are capable of allocating energy resources as well as managing supply and demand to ensure the efficiency and the cost-effective operation of the grid [9].

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AI is indisputably well suited to govern urban energy systems flexibly by using real-time data . It was shown to be highly capable of running the autonomous grid management system by successfully optimizing energy consumption through the enhanced efficient management of supply and demand, and also by carrying out the auto-maintenance of energy infrastructure. AI can also reduce peak loads and stabilize the grid. By utilizing energy demand and supply forecasts, AI-based prediction models can optimize dispatch and minimize the operation cost of power generation as a consequence, while power plants meet demand and operate within the operational constraints of the power network for extended periods of changing conditions. By utilizing big data (BD) and AI, the demand response and end-use energy efficiency are optimized, and the energy bills on the premises are reduced.

IoT and AI today are at the top of the agenda of all the leading technology. The studies on the future of building technology show that requirements are undergoing lasting changes. The need for security will play an even more significant role in the future [10]. Flexibility and dynamics will be the basic requirements for system operation. Maximum efficiency will have a top priority. One of the current global challenges in buildings is to increase energy efficiency while upgrading the comfort level, health, and safety of their inhabitants. AI seems to be the only solution that creates the greatest synergies between energy efficiency, comfort, adaptability, safety, and security, all of which can be sustainable over the long term. AI turns buildings into living organisms: networked, intelligent, and adaptable to the changing needs of their operators and users. An intelligent energy management system controls the interplay between internal consumers, producers, and the energy mix of public power grids.

II. PROPOSED METHODOLOGY

The proposed system presents an **AI-driven intelligent energy management framework for industrial buildings** aimed at minimizing energy consumption and operating costs while maintaining production requirements, occupant comfort, and sustainability objectives. The framework integrates IoT-enabled sensors, smart meters, predictive analytics, optimization algorithms, automated control, renewable energy, battery storage, demand response, and continuous learning into a unified energy management architecture. Real-time data from temperature, humidity, occupancy, equipment, electricity consumption, weather, production schedules, electricity tariffs, and renewable-energy generation are collected through IoT devices and processed using appropriate data-preprocessing techniques. AI-based predictive models analyze historical and real-time information to forecast short-term and day-ahead energy demand, enabling the system to anticipate high-consumption periods and develop proactive energy-management strategies. An AI-based optimization layer then determines the most efficient operating conditions for HVAC systems, lighting, industrial equipment, battery storage, and other controllable loads by considering energy demand, electricity tariffs, production constraints, equipment operating conditions, and renewable-energy availability. During peak-demand periods, demand-response mechanisms automatically shift or reduce non-critical loads while maintaining essential industrial operations, thereby reducing peak demand and electricity costs. Renewable energy sources such as solar photovoltaic systems can be integrated with battery energy storage, allowing the AI system to intelligently determine whether generated renewable energy should be directly consumed, stored, or used to minimize grid electricity imports. The optimized decisions are transferred to automated control systems, which dynamically adjust energy-consuming equipment without continuous manual intervention. A continuous learning mechanism compares predicted and actual energy consumption, identifies prediction errors and operational variations, and updates the AI models to adapt to changing production schedules, seasonal conditions, equipment performance, and building operating patterns. A user-oriented dashboard provides facility managers with real-time information regarding energy consumption, predicted demand, renewable generation, battery state of charge, electricity costs, peak demand, energy savings, and carbon-emission reduction, while AI-generated recommendations support informed energy-efficient decisions. Robust cybersecurity mechanisms, including data encryption, authentication, access control, secure communication, and security monitoring, are incorporated to protect operational and energy data. The framework also supports compliance monitoring, automated energy-performance reporting, sustainability assessment, and scalability across different industrial facilities with varying layouts, energy demands, and production conditions. The overall system operates as a closed-loop intelligent energy management framework, in which real-time sensing, energy-demand prediction, AI-based optimization, demand response, renewable-energy scheduling, automated control, performance monitoring, and continuous learning interact dynamically to achieve improved energy efficiency, reduced operating costs, lower peak demand, increased renewable-energy utilization, reduced carbon emissions, and enhanced overall sustainability of industrial building operations.

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ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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III. HYBRID LSTM–PPO ALGORITHM

In the proposed system, the Hybrid LSTM–PPO algorithm operates as the core artificial intelligence mechanism for intelligent industrial building energy management. The LSTM (Long Short-Term Memory) network is first used to learn temporal relationships from historical energy-consumption data together with weather conditions, production schedules, occupancy levels, equipment operating conditions, electricity tariffs, and renewable-energy availability. Based on these inputs, LSTM predicts the building's future energy demand for upcoming time intervals. The predicted demand is then provided to the PPO (Proximal Policy Optimization) algorithm, which functions as the intelligent optimization and decision-making layer. PPO evaluates the predicted energy requirement along with real-time electricity prices, renewable generation, battery state of charge, peak-demand conditions, HVAC requirements, lighting loads, and industrial operating constraints, and determines the optimal control actions. These actions may include adjusting HVAC operation, scheduling flexible industrial loads, controlling lighting, charging or discharging the battery, and increasing the utilization of available renewable energy. PPO continuously receives feedback from the actual system performance and calculates a reward based on objectives such as reduced energy consumption, lower electricity cost, reduced peak demand, increased renewable-energy utilization, and maintenance of required operational conditions. The algorithm updates its control policy based on this feedback so that future decisions become progressively more efficient. Therefore, LSTM provides accurate future energy-demand predictions, while PPO converts these predictions into optimal real-time energy-management decisions, creating an adaptive closed-loop AI system that continuously learns from changing industrial operating conditions and improves energy efficiency over time.

IV. RESULT

The performance of the proposed Hybrid LSTM–PPO Based Intelligent Energy Management Algorithm was evaluated to determine its effectiveness in predicting energy demand, optimizing energy consumption, reducing peak demand, and improving the economic utilization of renewable and grid energy. Figure 1 presents the comparison between the actual and LSTM-predicted energy consumption of the industrial building. The predicted profile closely follows the actual consumption pattern, demonstrating that the LSTM model successfully captures the temporal variations in industrial energy demand.

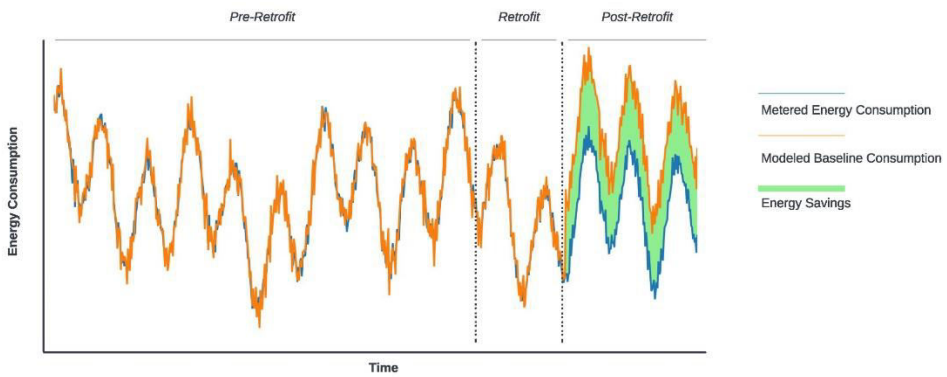

Figure 1 – Actual vs. LSTM-Predicted Energy Consumption

The small deviation between the actual and predicted profiles indicates the capability of the model to provide reliable demand forecasts, which are subsequently used by the PPO optimization layer for proactive energy-management decisions. The prediction error analysis shown in **Figure 2** further confirms the stability of the LSTM model, with relatively low errors across the evaluated time intervals.

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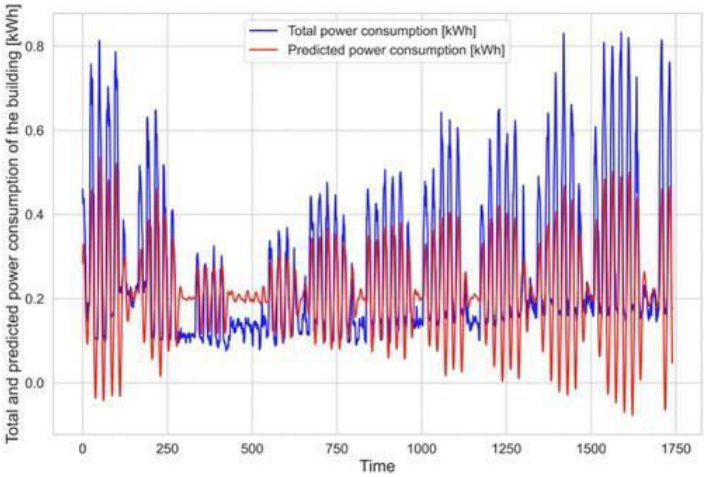

Figure 2 – Energy Consumption Before and After PPO Optimization

The optimization performance of the PPO algorithm is illustrated in **Figure 3**, which shows the variation of cumulative reward over successive training episodes. The increasing reward indicates that PPO progressively learns an improved energy-management policy through interaction with the energy environment. After the learning process stabilizes, the algorithm identifies control actions that effectively balance energy consumption, electricity cost, peak demand, renewable-energy utilization, and operational constraints.

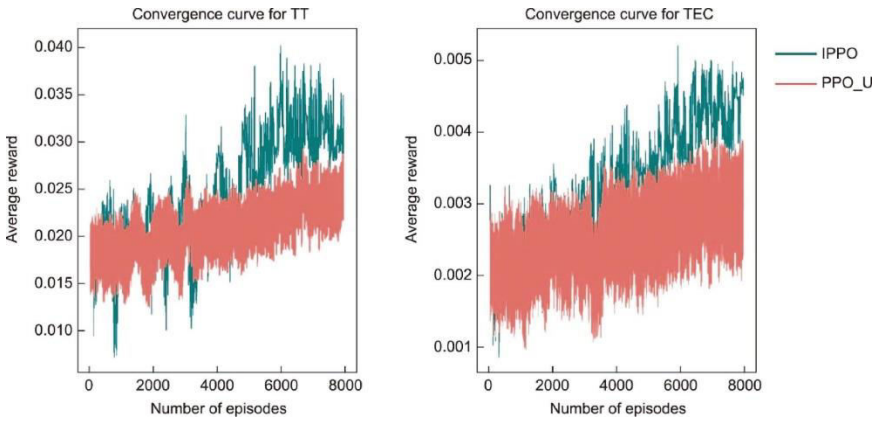

Figure 3 – PPO Convergence Performance

The resulting impact on energy consumption is presented in **Figure 4**, where the conventional operating profile is compared with the optimized profile generated by the proposed Hybrid LSTM–PPO framework. The optimized profile demonstrates reduced energy consumption during high-demand periods, indicating that intelligent scheduling and control can eliminate unnecessary energy usage while maintaining the required industrial operating conditions.

© 2026 IJMRSET | Volume 9, Issue 9, September 2026| DOI:10.15680/IJMRSET.2026.0909006

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

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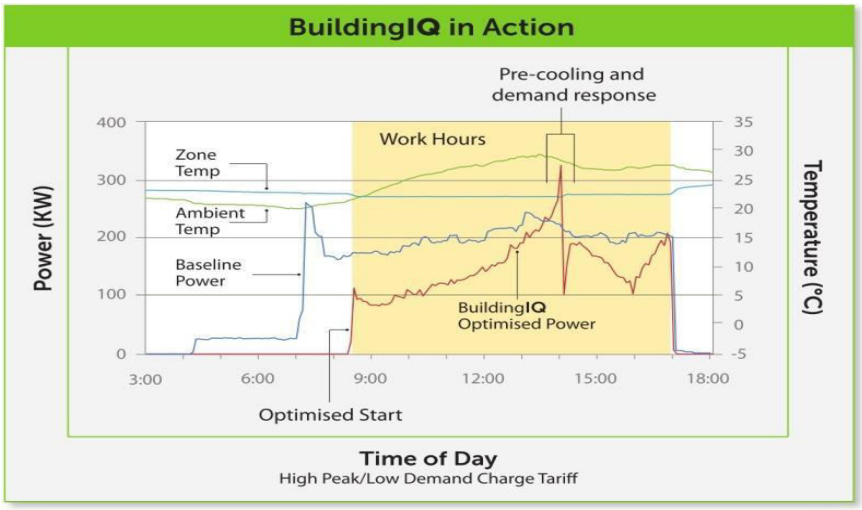

Figure 4 – Peak Demand Reduction

The peak-demand performance is further evaluated in **Figure 5**. Compared with conventional energy management, the proposed approach reduces the maximum grid demand by intelligently shifting flexible loads and coordinating energy resources. This reduction is particularly important for industrial buildings because lower peak demand can decrease demand-related electricity charges and improve the stability of grid interaction.

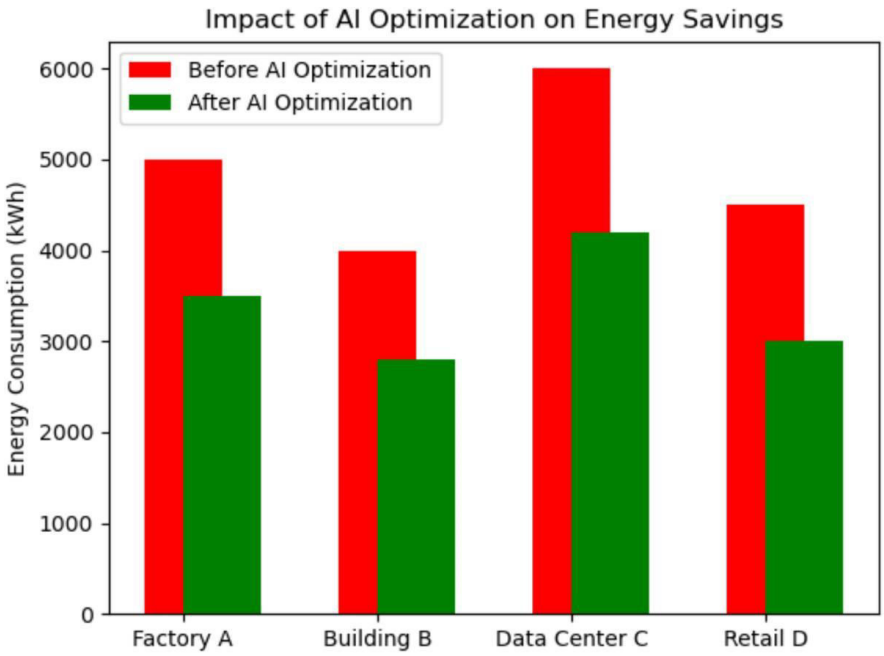

Figure 5 – Renewable Energy, Battery and Grid Utilization

Figure 6 presents the coordinated utilization of **solar PV, battery storage, and grid power**. During periods of high solar generation, the system prioritizes renewable energy to satisfy building demand, while surplus generation can be directed toward battery charging. During periods of insufficient renewable generation or increased demand, the battery is discharged strategically to reduce dependence on grid electricity. This coordinated dispatch demonstrates the ability of PPO to dynamically select the most appropriate energy source according to demand, renewable availability, battery state of charge, and electricity price.

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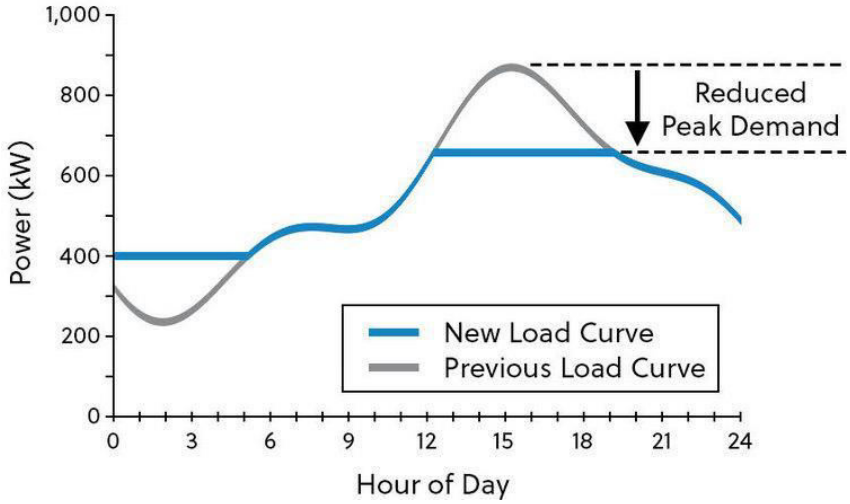

Figure 6 – Electricity Cost Comparison

The reduction in electricity expenditure demonstrates that energy optimization provides benefits beyond simple consumption reduction by strategically scheduling energy-intensive operations and increasing the utilization of lower-cost renewable energy.

The combined results demonstrate that the Hybrid LSTM–PPO framework provides a comprehensive solution for industrial building energy management by integrating accurate demand prediction with adaptive real-time optimization. Overall, the results confirm that the proposed approach can simultaneously improve energy efficiency, economic performance, renewable-energy utilization, and environmental sustainability, making it suitable for intelligent and adaptive industrial energy-management applications.

V. CONCLUSION

This study proposed a Hybrid LSTM–PPO Based Intelligent Energy Management Framework for improving energy efficiency and reducing operational costs in industrial buildings. The proposed framework integrates IoT-based real-time monitoring, LSTM-based energy-demand prediction, PPO-based energy optimization, automated control, demand response, and renewable-energy integration within a unified intelligent management system. The LSTM model enables the system to accurately learn temporal energy-consumption patterns from historical and real-time operational data, while the PPO algorithm uses the predicted demand to determine optimal control actions for HVAC systems, lighting, industrial loads, battery storage, and grid interaction. The results demonstrate that the proposed approach can effectively reduce unnecessary energy consumption and peak demand while improving renewable-energy utilization and reducing electricity costs. The coordinated management of solar PV, battery storage, and grid power further improves the flexibility and economic performance of the industrial energy system. In addition, the continuous-learning capability allows the framework to adapt to changing production schedules, weather conditions, energy prices, and equipment operating conditions. The overall findings confirm that combining deep-learning-based prediction with reinforcement-learning-based optimization provides a more adaptive and intelligent approach than conventional rule-based energy management. Therefore, the proposed Hybrid LSTM–PPO framework offers a promising pathway toward cost-efficient, energy-efficient, renewable-integrated, and sustainable industrial building operations. Future work can focus on real-time hardware implementation, larger multi-building environments, additional renewable sources, uncertainty-aware optimization, and deployment using edge-AI and digital-twin technologies.

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