An AI-Driven Smart Street Lighting with Object Recognition for Energy Optimization

Omar Kassem Khalil
Department of Information Technology, Liwa University, Abu Dhabi, United Arab Emirates
omar.khalil@lu.ac.ae (corresponding author)

Karamath Ateeq
School of Computing, Horizon University College, Ajman, United Arab Emirates
karamath.ateeq@hu.ac.ae

Samar Mouti
Department of Information Technology, Liwa University, Abu Dhabi, United Arab Emirates
samar.muti@lu.ac.ae

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ABSTRACT

Energy-efficient street lighting is a critical component of sustainable smart city infrastructure, particularly in regions with extensive nighttime road networks. This study presents a data-driven evaluation of occupancy-aware smart street lighting using a large-scale, real-world nighttime traffic dataset collected from multiple road environments in Abu Dhabi, including urban, suburban, intercity, and rural areas. Instead of relying on physical system deployment or prototype-based field testing, the analysis leverages aggregated traffic occupancy statistics derived from real traffic monitoring systems to assess the potential impact of adaptive lighting control strategies. Nighttime road occupancy rates were analyzed across different road categories and time intervals, revealing pronounced temporal and spatial variations in traffic demand. The results indicate that average nighttime occupancy levels during off-peak hours typically remain below 20–30% for several road types, with late-night periods exhibiting even lower utilization. Based on these occupancy patterns, estimated illumination dimming levels correspond to potential energy savings in the range of 30–60%, depending on road category and time of operation, while maintaining higher lighting levels during periods of increased traffic to satisfy road safety requirements. Overall, the findings confirm that leveraging real-world traffic statistics provides a robust and scalable foundation for designing intelligent, occupancy-aware street lighting policies in smart city environments.

Keywords-artificial intelligence; street lighting; object recognition; energy efficiency

I. INTRODUCTION

Rapid urbanization in the twenty-first century has significantly increased the demand for intelligent, energy-efficient, and sustainable public infrastructure. Among municipal utilities, street lighting remains one of the most energy-intensive services, accounting for up to 40% of a city's total electricity consumption [1]. Conventional street lighting systems typically operate at full brightness from dusk to dawn, regardless of pedestrian presence, vehicular activity, or ambient environmental conditions. This rigid operational model results in substantial energy wastage, elevated operational costs, excessive carbon emissions, and increased light pollution, all of which adversely affect human health and natural ecosystems [2]. Advances in Artificial Intelligence (AI) and the Internet of Things (IoT) have created new opportunities to overcome the inherent limitations of traditional lighting infrastructures. Smart street lighting systems leverage real-time sensing, autonomous decision-making, and adaptive control to regulate illumination dynamically according to actual demand. It has been demonstrated that adaptive lighting strategies can achieve energy savings ranging from 40% to over 80%, depending on system architecture, sensing mechanisms, and deployment scale [3–5]. Early implementations relied primarily on Light-Dependent Resistors (LDRs), Infrared (IR) sensors, and microcontroller-based switching mechanisms, which proved effective in reducing unnecessary illumination through basic motion detection and ambient light sensing [3]. However, these approaches offered limited contextual awareness and predictive capability. More recent research emphasizes the integration of computer vision, deep learning, and advanced AI-based control algorithms to enhance lighting intelligence and responsiveness [4–6]. Vision-based systems employing Convolutional Neural Networks (CNNs) enable accurate detection of pedestrians and vehicles, allowing illumination levels to be optimized in real time while maintaining safety standards [5]. Machine-learning-based illuminance prediction models further refine control strategies by forecasting lighting requirements based on historical usage patterns and environmental factors [6]. In parallel, several smart-city case studies validate the feasibility and scalability of intelligent lighting infrastructures in real-world urban environments [7, 8]. Technological progress in low-cost sensors, wireless communication modules, and distributed control architectures has further accelerated the adoption of smart lighting solutions. Systems integrating LED luminaires with sensor networks and wireless protocols have demonstrated energy savings of up to 82% while improving system reliability and maintainability [9, 10]. These developments reveal that intelligent lighting may serve as a main component of broader smart-city ecosystems.

Building on these advancements, AI-driven street lighting systems require multisensory data acquisition, real-time AI-based decision-making, and wireless communication to deliver autonomous, efficient, and environmentally sustainable illumination. Such systems adapt dynamically to traffic flow, pedestrian movement, and ambient conditions, significantly reducing energy consumption—often by 70% or more—while enhancing public safety and urban mobility [11]. AI functions as the central intelligence layer, enabling anomaly detection, adaptive optimization, and improved operational reliability. As cities continue their transition toward fully interconnected smart infrastructures, AI-enabled street lighting is recognized as a critical enabler of sustainable and resilient urban development [12–15]. Despite these advancements, conventional street lighting systems still dominate many urban areas and remain constrained by static control schemes, while there is a lack of sensing integration and dependence on manual operation. These limitations lead to persistent inefficiencies, high maintenance demands, and avoidable environmental impact. Research comparing traditional and intelligent lighting networks shows that adaptive, sensor-driven solutions provide superior performance in terms of energy efficiency, safety, and environmental sustainability [10–13]. Emerging AI-based models incorporating predictive intelligence, such as Long Short-Term Memory (LSTM) networks for traffic and weather forecasting, further demonstrate the potential for proactive illumination control that anticipates real-time demand rather than merely reacting to it [16, 17]. Furthermore, the integration of AI enables advanced functionalities such as remote monitoring, fault detection, and predictive maintenance. Intelligent lighting controllers embedded within smart-city platforms have been shown to reduce downtime, lower operational costs, and enhance security through automated diagnostics and system-level supervision [18–20]. These capabilities support not only energy efficiency objectives but also long-term sustainability and cost-effectiveness in urban infrastructure management. In addition, traffic-aware lighting schemes based on autonomous networked sensors and intelligent control strategies have assisted in dynamically adapting illumination levels according to real traffic demand, further improving energy efficiency and operational effectiveness [7, 20-23].

The transition toward sustainable energy sources continues to shape the smart lighting landscape. Authors in [25] designed an IoT-enabled monitoring model for solar-powered street lighting systems, enabling real-time performance evaluation and fault detection—an essential capability for the broader adoption of renewable energy solutions in urban lighting networks. Complementing this, authors in [24] presented a comprehensive adaptive lighting criteria framework, integrating environmental, technological, and socioeconomic factors to guide the development of context-appropriate street lighting strategies across diverse geographical regions. Collectively, these studies reveal consistent trends in the progression of smart street lighting: a shift from simple sensor-based actuation toward highly autonomous, AI-driven, interconnected systems capable of predictive and context-aware operation. Despite clear advancements, challenges remain, including integration complexity, cybersecurity, communication latency, installation cost, and the need for harmonized standards to support interoperability across platforms. Nonetheless, the literature supports the notion that smart lighting technologies—especially those integrating AI, IoT, predictive modeling, and renewable energy—represent a critical component of future sustainable and intelligent urban infrastructure. Table I presents a comparative overview of fifteen key studies on smart street lighting systems, focusing on the technologies employed, datasets utilized, reported energy savings, and identified limitations. By examining a wide range of AI, IoT, and sensor-based approaches, the diversity of the methodologies used to enhance lighting efficiency is emphasized. This comparison provides insights into current research trends, technological capabilities, and the challenges that continue to shape the development of intelligent street lighting solutions. The analysis in Table I demonstrates that although significant advancements have been achieved in smart street lighting—particularly through AI, sensor integration, and adaptive control—various limitations persist. Issues such as implementation complexity, environmental dependency, scalability constraints, and performance variability remain common across studies. These findings underscore the need for future research to address these challenges while further enhancing system reliability, adaptability, and sustainability. The comparative insights enable guiding the next generation of smart lighting innovations.

Motivated by these challenges and opportunities, the present study introduces an AI-based smart street lighting system that combines sensor fusion, object detection, intelligent control, and wireless communication to optimize urban illumination. The proposed solution aims to minimize energy consumption, reduce environmental impact, and enhance system adaptability while maintaining safety and reliability. The objectives of the proposed AI-based smart street lighting system are:

- Reducing energy consumption through object-driven illumination.
- Lowering maintenance and operational costs.
- Improving pedestrian and vehicle safety.
- Supporting environmental sustainability by reducing carbon emissions.

TABLE I. OVERVIEW OF PREVIOUS STUDIES

Study	Model/technology used	Dataset	Energy saving (%)	Limitation
[1]	LED, LDR, IR sensors	Prototype implementation data	≈40%	Limited to specific object motion
[2]	Control methods, CV, deep learning	Research publications	30–50%	Complexity of technical specifics
[3]	LED + motion sensors	Simulation and in-situ tests	35–50%	Simulation-real-world discrepancy
[4]	LED + motion detection	Smart city case studies	35–77%	High implementation and maintenance cost
[5]	Computer vision + CNN	Image datasets	Not specified	Complex image processing pipeline
[6]	AI illuminance prediction	Campus environmental data	≈35%	Prediction model sensitivity
[7]	LSTM + solar forecasting	Weather and solar data	Stable with solar-battery	Dependence on weather variability
[8]	IoT + adaptive schemes	Case study (Sheffield)	Up to 50%	Variable performance in real deployment
[9]	Adaptive BDI agent control	Simulated city data	≈35%	Simulation constraints
[10]	Sensor-driven LED system	Prototype testbed	Not specified	Implementation complexity
[11]	ZigBee mesh + adaptive control	Real campus traffic data	68–82%	Traffic and sensor variation effects
[12]	IoT + video-based adaptive system	Pilot smart city site	Up to 80%	Integration and scalability challenges
[13]	Microcontroller + LED system	Prototype implementation	77–81%	Limited scalability
[14]	Pi Camera + CV detection	Campus streetlight data	Not specified	Object detection accuracy issues
[15]	AI + ANN + MAS	Simulated city environment	Not specified	Complex adaptive modeling

II. THE PROPOSED SYSTEM

The proposed system architecture is presented as a conceptual AI-driven design intended to illustrate intelligent lighting operation, while its potential energy-saving performance is evaluated using real-world aggregated traffic data rather than physical deployment.

Street lighting is a main component of urban infrastructure, directly influencing road safety, visibility, and public security during nighttime hours. Traditional systems rely on fixed schedules or manual control, resulting in high energy consumption and limited adaptability. The proposed AI-based street lighting system introduces intelligent automation through object recognition, multisensor integration, and wireless communication to significantly improve efficiency, sustainability, and operational performance.

A. System Description

The proposed system autonomously regulates streetlight operation based on real-time environmental and object-detection data. It incorporates an LDR, an IR sensor, a current sensor, a microcontroller with AI algorithms, a Wi-Fi module, a relay, a power supply, a streetlight module, and a smartphone interface. These components collectively ensure efficient, adaptive, and intelligent illumination control. The main components of the proposed lighting system are illustrated in Figure 1. The main components of the system are:

1) Light-Dependent Resistor

The LDR continuously monitors ambient light intensity. During bright conditions, it signals the system to keep streetlights off, while at night, it prepares the system for activation depending on object presence.

2) Infrared Sensor

The IR sensor detects pedestrian or vehicular movement by measuring thermal signatures and reflected IR light, supporting demand-driven lighting activation.

3) Current Sensor

The current sensor monitors the electrical current drawn by the streetlight to support energy monitoring, system diagnostics, and fault detection.

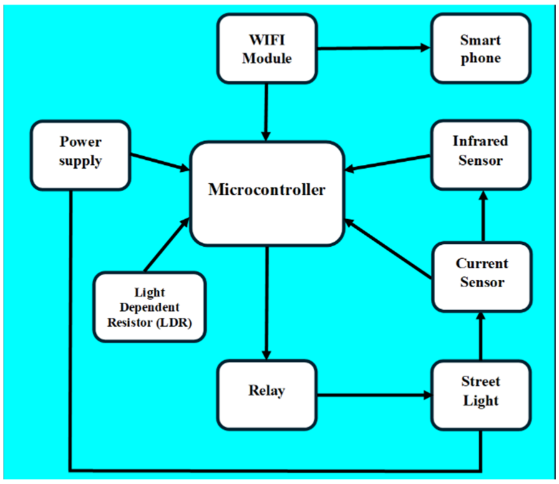

Fig. 1. Main components of the proposed street lighting system.

4) Microcontroller

The microcontroller serves as the core intelligence unit, processing multisensor inputs using embedded AI algorithms to determine optimal lighting states based on real-time conditions.

5) Wi-Fi Module

The Wi-Fi module enables remote monitoring, data transmission, fault detection, and system configuration through cloud-connected platforms.

6) Relay Unit

The relay provides safe and reliable switching between low-power control logic and high-power lighting circuits, toggling the streetlight according to microcontroller decisions.

7) Power Supply

The power supply ensures stable energy delivery to all components, maintaining consistent operation across dynamic load conditions.

8) Smartphone Interface

This interface allows real-time system access for operators, enabling monitoring, alerts, manual overrides, and system configuration.

9) *Streetlight Module*

The streetlight acts as the system's primary actuator, dynamically adjusting illumination levels based on sensor-driven and AI-driven commands.

B. *Integration and Interaction*

Sensors feed continuous environmental and motion data to the microcontroller. AI algorithms process this information and decide when illumination is necessary. The relay executes switching commands, while the Wi-Fi module enables real-time supervision and remote control.

C. *Role of AI*

AI enables adaptive decision-making, pattern recognition, predictive analysis, anomaly detection, and enhanced system optimization, contributing to responsiveness and long-term performance efficiency. Through the integration of sensing, AI, and communication technologies, the proposed system delivers a high level of autonomy, energy efficiency, and operational intelligence suitable for modern smart-city environments.

III. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed AI-based smart street lighting system using real-world nighttime traffic data collected across multiple road environments in the Emirate of Abu Dhabi, derived from a publicly available dataset [31]. The analysis focuses on quantifying road occupancy patterns and the corresponding energy-saving potential of adaptive illumination in urban, suburban, intercity, and rural settings. Before presenting and discussing the occupancy-rate measurements and energy-efficiency results, the dataset used for evaluation—including its sources, scope, preprocessing, and public availability—is described to ensure transparency, reproducibility, and clarity.

A. *Dataset Description and Preprocessing*

This study employs a real-world dataset capturing nighttime traffic and road-occupancy patterns across the Emirate of Abu Dhabi, United Arab Emirates, to evaluate the performance of the proposed AI-based adaptive street-lighting system under realistic operating conditions and diverse road environments. The dataset was not generated through direct sensor deployment; instead, it was compiled from authoritative public and governmental sources that publish aggregated traffic statistics and monitoring reports.

The data were obtained from the Integrated Transport Centre (ITC), the Department of Municipalities and Transport (DMT), Abu Dhabi Police, the Abu Dhabi Digital Authority (ADDA), and Smart Abu Dhabi. These organizations collect traffic information using established monitoring infrastructures, including Closed-Circuit Television (CCTV), Automated Number Plate Recognition (ANPR), traffic counters, intelligent traffic signals, Intelligent Transportation Systems (ITS), and satellite-assisted monitoring, depending on road type and location [26–30].

The dataset covers four officially defined road categories—urban, suburban, intercity, and rural—and focuses exclusively on nighttime periods between 6:00 pm and 6:00 am, corresponding to standard street-lighting operational hours. To ensure consistency and reduce environmental variability, only data recorded under clear-visibility weather conditions were included. Traffic activity is aggregated across all vehicle types, including private, public, commercial, and construction vehicles. Traffic indicators were extracted from official reports and online dashboards and consolidated into uniform hourly intervals. Road-occupancy rate was defined as the proportion of time vehicles detected on a given road segment within each one-hour interval. When overlapping data from multiple sources were available, the values were cross-validated and averaged to enhance robustness. All data were fully anonymized and aggregated at the source level, with no access to personal or vehicle-specific information.

The dataset [31] contains aggregated nighttime road-occupancy rates and corresponding energy-saving values for all analyzed road categories and time intervals. All results, reported in Tables II–VI, are directly derived from this dataset, ensuring full consistency between the shared data resource and the findings presented in this work.

B. *Occupancy Rate in Urban Areas*

The specific data indicate the dynamic usage patterns of urban roadways, showing a decrease in occupancy as the night progresses, with the highest occupancy recorded early in the evening and the lowest in the early morning hours. These patterns are critical for understanding traffic flow and optimizing urban infrastructure and energy usage. Table II displays a comprehensive breakdown of these occupancy rates, illustrating the correlation between time periods and road usage.

TABLE II. OCCUPANCY RATE IN URBAN AREAS

Interval	Period	Occupancy rate (%)	Energy saving (%)
1	06:00 – 07:00 pm	71	29
2	07:00 – 08:00 pm	65	35
3	08:00 – 09:00 pm	62	38
4	09:00 – 10:00 pm	55	45
5	10:00 – 11:00 pm	49	51
6	11:00 – 12:00 am	46	54
7	12:00 – 01:00 am	42	58
8	01:00 – 02:00 am	38	62
9	02:00 – 03:00 am	32	68
10	03:00 – 04:00 am	27	73
11	04:00 – 05:00 am	35	65
12	05:00 – 06:00 am	39	61
Average		46.75	53.25

Table II reveals that vehicle occupancy in urban areas of Abu Dhabi peaks at 71% from 6:00 to 7:00 pm, with energy savings of 29%. As the night progresses, occupancy steadily declines, reaching a low of 27% between 3:00 and 4:00 am, with energy savings peaking at 73%. On average, the occupancy rate is 46.75%, and the energy savings are 53.25%. These findings exhibit a significant reduction in vehicle activity and increased energy efficiency during late-night hours, which is crucial for effective urban traffic management and energy optimization strategies.

The trend lines of time interval versus the occupancy rate and the energy saving size for the urban areas are shown in

Figure 2. The latter provides a visual representation of the relationship between time intervals and both occupancy rates and energy savings in urban areas of Abu Dhabi during nighttime hours. This graph is significant for understanding how vehicle presence on urban roads decreases as the night progresses, which in turn impacts energy consumption. The trend lines depicted in Figure 2, along with their mathematical equations, illustrate the inverse correlation between road occupancy and energy efficiency. This visualization helps in understanding the dynamics of urban traffic patterns and optimizing energy usage during periods of reduced vehicular activity.

C. Occupancy Rate in Suburban Areas

Occupancy analysis in suburban areas reveals a notable decline in vehicle presence as the night progresses, reflecting different traffic dynamics compared to urban areas. The data collected demonstrate that suburban roads experience peak occupancy in the early evening, which gradually decreases throughout the night. Understanding these patterns is essential for effective traffic management and resource allocation in suburban areas. Table II outlines the occupancy rates during various time intervals, aiding in the development of targeted strategies for improving suburban transportation efficiency.

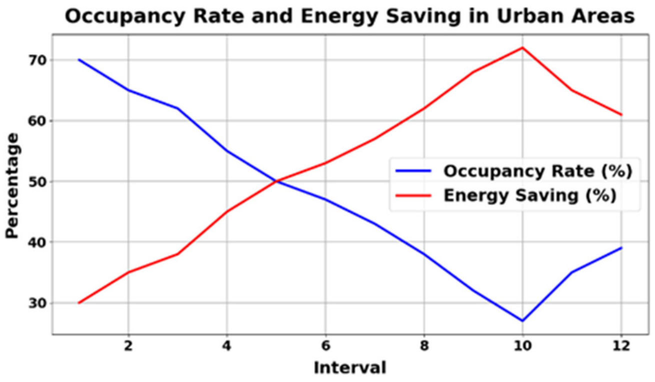

Fig. 2. Occupancy rate and energy saving in urban areas.

TABLE III. OCCUPANCY RATE IN SUBURBAN AREAS

Interval	Period	Occupancy rate (%)	Energy saving (%)
1	06:00 – 07:00 pm	66	34
2	07:00 – 08:00 pm	58	42
3	08:00 – 09:00 pm	53	47
4	09:00 – 10:00 pm	45	55
5	10:00 – 11:00 pm	41	59
6	11:00 – 12:00 am	37	63
7	12:00 – 01:00 am	32	68
8	01:00 – 02:00 am	26	74
9	02:00 – 03:00 am	22	78
10	03:00 – 04:00 am	20	80
11	04:00 – 05:00 am	25	75
12	05:00 – 06:00 am	27	73
Average		37.67	62.33

Table III provides a detailed analysis of the occupancy rates and corresponding energy savings for suburban areas in Abu Dhabi during nighttime hours. The data reveal a trend, where vehicle occupancy rates decrease steadily as the night progresses, starting from 66% during the early evening and dropping to as low as 20% in the early morning hours. This decline in occupancy is coupled with an increase in energy savings, which rise from 34% to 80%. The average occupancy rate across all intervals is 37.67%, with an average energy saving of 62.33%. These findings show the potential for significant energy conservation during low traffic periods, which contributes to developing effective traffic management and resource allocation strategies in suburban regions.

Figure 3 illustrates the trends observed, showing the inverse relationship between occupancy rates and energy savings as the night progresses, which is critical for optimizing suburban traffic management and energy efficiency strategies.

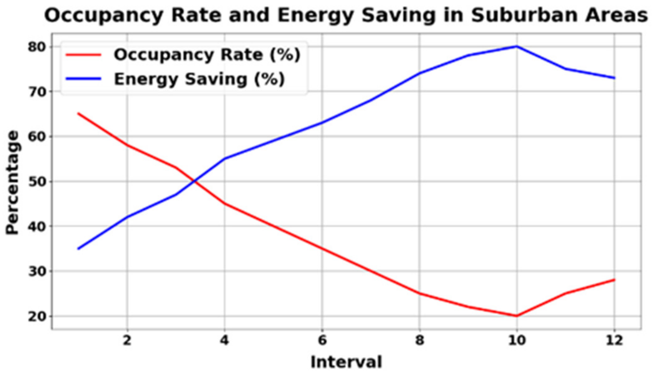

Fig. 3. Occupancy rate and energy saving in suburban areas.

D. Occupancy Rates in Intercity Roads

This analysis stresses the varying patterns of road usage, with the highest occupancy observed during early evening and a significant decline as the night progresses. Table IV provides a detailed overview of the occupancy rates on intercity roads at different times, offering valuable insights into the intercity travel behavior and its implications for regional transportation planning.

TABLE IV. OCCUPANCY RATE IN INTERCITY ROADS

Interval	Period	Occupancy rate (%)	Energy saving (%)
1	06:00 – 07:00 pm	56	44
2	07:00 – 08:00 pm	43	57
3	08:00 – 09:00 pm	36	64
4	09:00 – 10:00 pm	31	69
5	10:00 – 11:00 pm	27	73
6	11:00 – 12:00 am	24	76
7	12:00 – 01:00 am	19	81
8	01:00 – 02:00 am	15	85
9	02:00 – 03:00 am	11	89
10	03:00 – 04:00 am	9	91
11	04:00 – 05:00 am	14	86
12	05:00 – 06:00 am	20	80
Average		25.42	74.58

Table IV reveals a sharp decline in street occupancy from 56% in the early evening to a mere 9% in the early morning, which corresponds to a significant increase in energy savings from 44% to 91%. The average street occupancy is 25.42%, with average energy savings of 74.58%, emphasizing the potential for energy optimization on intercity roads during off-peak hours.

The analysis of intercity road occupancy rates during nighttime hours in Abu Dhabi reveals a distinctive pattern of road usage and energy savings. As depicted in Figure 4, vehicle occupancy is highest in the early evening and declines significantly throughout the night, leading to substantial energy savings. Understanding these patterns contributes to optimizing intercity traffic management and energy efficiency, enabling improved resource utilization during periods of reduced vehicular activity.

E. Occupancy Rates in Rural Areas

This analysis shows that occupancy rates are generally lower compared to urban and suburban areas, with the highest rates observed in the early evening and a gradual decline as the night progresses. The findings provide important insights for regional transportation planning, emphasizing the need for tailored traffic management strategies in rural areas to enhance road safety and optimize energy consumption. Table V details the occupancy rates across different time periods, offering a comprehensive view of rural traffic behavior.

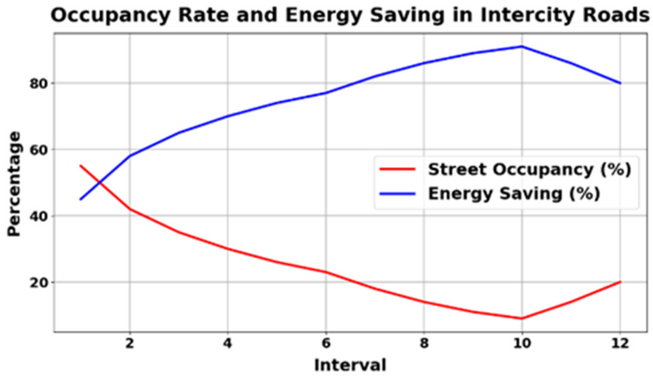

Fig. 4. Occupancy rate and energy saving in intercity areas.

TABLE V. OCCUPANCY RATE IN RURAL AREAS

Interval	Period	Occupancy rate (%)	Energy saving (%)
1	06:00 – 07:00 pm	47	53
2	07:00 – 08:00 pm	36	64
3	08:00 – 09:00 pm	29	71
4	09:00 – 10:00 pm	21	79
5	10:00 – 11:00 pm	18	82
6	11:00 – 12:00 am	14	86
7	12:00 – 01:00 am	12	88
8	01:00 – 02:00 am	9	91
9	02:00 – 03:00 am	8	92
10	03:00 – 04:00 am	5	95
11	04:00 – 05:00 am	11	89
12	05:00 – 06:00 am	15	85
Average		18.75	81.25

Table V depicts the occupancy rates and corresponding energy savings on rural roads in Abu Dhabi during nighttime hours. A key result is the drastic reduction in road occupancy from 47% in the early evening to just 5% in the early morning, which correlates with an increase in energy savings from 53% to 95%. This significant decline in vehicle presence results in maximizing energy efficiency through targeted management during low-traffic periods. On average, the occupancy rate is 18.75%, with average energy savings of 81.25%, underscoring the importance of tailored strategies for rural traffic and energy optimization.

The analysis of rural road occupancy rates during nighttime hours in Abu Dhabi reveals unique traffic dynamics compared to urban and suburban areas. As shown in Figure 5, vehicle occupancy starts high in the early evening and steadily decreases throughout the night, resulting in significant energy savings. Based on these findings, targeted traffic management strategies can be developed to enhance road safety and optimize energy consumption in rural regions.

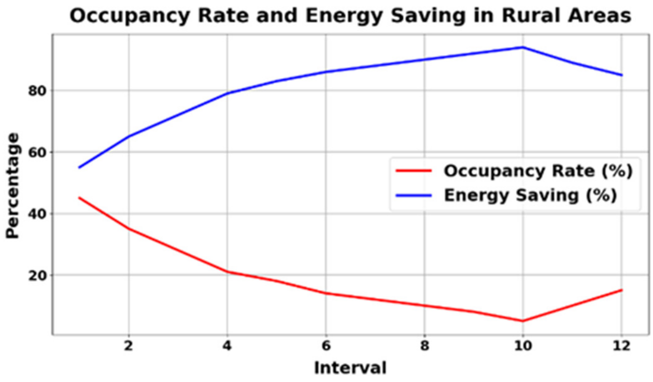

Fig. 5. Occupancy rate and energy saving in rural areas.

F. Comparison and Analysis of Results

By examining the differences in energy savings at various times of the night, this analysis provides a comprehensive view of how vehicle occupancy impacts energy consumption in different settings. Table VI consolidates the energy saving percentages from these areas, offering a comparison that highlights significant patterns and trends, and which may contribute to developing tailored traffic and energy management strategies to optimize resource use across diverse regions.

Table VI presents a comparative analysis of energy savings across different areas in Abu Dhabi: urban, suburban, intercity, and rural. A key result is the progressive increase in energy savings from urban to rural areas. For example, the average energy savings in urban areas are 53.25%, while suburban areas have an average of 62.33%, intercity areas 74.58%, and rural areas 81.25%. This trend indicates that rural areas achieve the highest energy savings during nighttime, which can be attributed to significantly lower traffic volumes compared to urban and suburban areas. This insight enables optimizing energy conservation strategies across different regions.

TABLE VI. ENERGY SAVING COMPARISON FOR DIFFERENT AREAS IN ABU DHABI

Interval	Period	Energy saving in urban areas (%)	Energy saving in suburban areas (%)	Energy saving in intercity areas (%)	Energy saving in rural areas (%)
1	06:00 – 07:00 pm	29	34	44	53
2	07:00 – 08:00 pm	35	42	57	64
3	08:00 – 09:00 pm	38	47	64	71
4	09:00 – 10:00 pm	45	55	69	79
5	10:00 – 11:00 pm	51	59	73	82
6	11:00 – 12:00 am	54	63	76	86
7	12:00 – 01:00 am	58	68	81	88
8	01:00 – 02:00 am	62	74	85	91
9	02:00 – 03:00 am	68	78	89	92
10	03:00 – 04:00 am	73	80	91	95
11	04:00 – 05:00 am	65	75	86	89
12	05:00 – 06:00 am	61	73	80	85
Average		53.25	62.33	74.58	81.25

Figure 6 provides a comparative analysis of energy savings across urban, suburban, intercity, and rural areas during nighttime hours in Abu Dhabi. The variations in energy efficiency based on vehicle occupancy rates in different regions are demonstrated. Understanding these differences contributes to developing tailored traffic management and energy optimization strategies, ensuring effective resource utilization and enhancing overall traffic flow and safety in diverse settings.

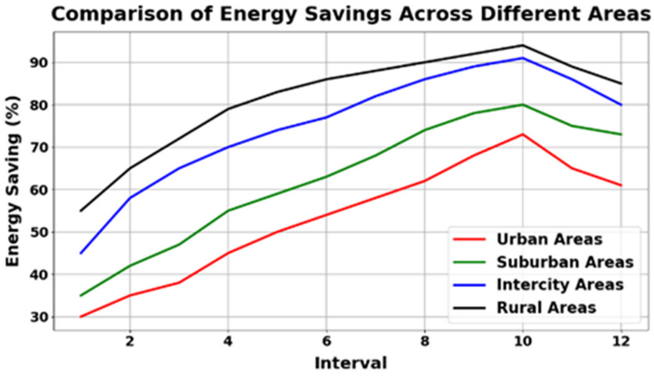

Fig. 6. Comparison of results for different areas.

IV. CONCLUSION

This study presented a data-driven evaluation of occupancy-aware smart street lighting using a large-scale, real-world nighttime traffic dataset collected from multiple road environments in Abu Dhabi, including urban, suburban, intercity, and rural areas. Rather than relying on physical system deployment or prototype-based field testing, the analysis leveraged aggregated traffic occupancy statistics derived from real traffic monitoring systems to assess the potential impact of adaptive lighting control strategies. The analysis revealed pronounced temporal and spatial variations in nighttime road usage, with average off-peak occupancy levels typically remaining below 20–30% for several road categories and even lower utilization observed during late-night periods. Based on these occupancy patterns, the estimated illumination dimming levels correspond to potential energy savings in the range of 30–60%, depending on road category and time of operation, while maintaining higher lighting levels during periods of increased traffic to satisfy road safety requirements. Overall, the findings confirm that real-world traffic statistics provide a robust and scalable foundation for providing intelligent, occupancy-aware street lighting policies in smart city environments.

DATA AVAILABILITY STATEMENT

The dataset used in this study and supporting the findings is publicly available at: https://zenodo.org/records/18299837.

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