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Performance Evaluation of Wireless Sensor Network Applications Using Grey Relational Analysis

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Abstract: *This paper evaluates Wireless Sensor Network (WSN) applications using the Grey Relational Analysis (GRA) method to determine their suitability for different domains. WSNs are critical in various fields, including Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems, each with specific performance requirements. The study focuses on four key performance criteria: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. These metrics are normalized, and the Grey Relational Coefficients (GRC) are calculated to assess the performance of each WSN application against the ideal values. The results reveal significant variations in performance across different applications. Smart Agriculture ranks first with a Grey Relational Grade (GRG) of 0.6394, excelling due to its strong balance across all criteria, particularly in Network Coverage and Response Time. Environmental Monitoring follows closely with a GRG of 0.6283, driven by its superior Energy Efficiency, although its lower Network Coverage affects its ranking. Healthcare Monitoring, with a GRG of 0.6168, ranks third, showing excellent Data Accuracy but lagging slightly in Energy Efficiency. Smart Home Systems, with a GRG of 0.5722, ranks fourth, demonstrating high Network Coverage but weaker Data Accuracy. Industrial Automation ranks lowest with a GRG of 0.4247, reflecting its subpar performance in Energy Efficiency and Response Time. This analysis highlights the strengths and weaknesses of each WSN application, providing valuable insights for selecting the most appropriate technology based on specific performance needs. The GRA method proves to be an effective tool for multi-criteria decision-making, enabling a comprehensive evaluation of WSN performance across diverse use cases. These findings are particularly useful for optimizing WSN deployments in environments with varying requirements for energy consumption, data precision, coverage, and responsiveness.*

Keywords: *Wireless Sensor Networks (WSN), Grey Relational Analysis (GRA), Energy Efficiency, Data Accuracy, Network Coverage, Response Time.*

1. INTRODUCTION

Wireless Sensor Networks (WSNs) represent a transformative technological innovation with a wide range of applications that significantly impact various sectors. These networks consist of spatially distributed sensor nodes that autonomously collect and transmit data to central locations for further analysis. WSNs are designed to operate under resource constraints such as limited energy, computational capacity, and bandwidth, yet they are highly efficient in providing real-time, context-aware information. This flexibility makes them suitable for deployment in remote, hostile, or inaccessible environments, opening up numerous possibilities for their use in diverse applications. In this article, we explore key areas where WSNs are applied, focusing on how they drive innovation in smart agriculture, environmental monitoring, healthcare, industrial automation, and smart home systems. One of the most significant applications of WSNs is in smart agriculture. Agriculture has always been subject to the uncertainties of nature, including erratic weather patterns, pest invasions, and inefficient resource management. WSNs provide farmers with the ability to make data-driven decisions to optimize crop yields, manage resources such as water and fertilizer, and

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predict environmental conditions. These systems often consist of sensors placed in fields to monitor soil moisture, temperature, and humidity levels. By transmitting real-time data, WSNs help in precision farming, enabling farmers to irrigate only when necessary, thus conserving water. Furthermore, they provide insights into crop health and detect early signs of pest infestations, allowing for timely interventions. This results in not only improved yields but also reduced input costs, which is crucial in both large-scale commercial farming and small-scale sustainable agriculture. The integration of WSNs with other technologies, such as drones and automated irrigation systems, has pushed the boundaries of modern farming techniques, transforming traditional practices into highly efficient, technology-driven processes. Smart agriculture enabled by WSNs ensures better resource utilization, enhanced productivity, and minimal environmental impact. Environmental monitoring is another critical domain where WSNs play a pivotal role. The need for real-time data collection in areas prone to natural disasters, pollution, or ecological degradation is paramount to ensure timely interventions and preventive measures. WSNs are deployed in forests, oceans, volcanoes, and urban areas to monitor various environmental parameters such as temperature, humidity, air quality, and seismic activity. For instance, in forested areas, WSNs can be used to detect early signs of forest fires by measuring temperature spikes and the presence of smoke particles. This information can be sent to authorities, allowing them to take action before the fire spreads uncontrollably. In urban environments, WSNs monitor air pollution levels, providing data that can be used to enforce regulations and create policies to improve air quality. Additionally, WSNs have been utilized in marine environments to track changes in water temperature and pH levels, which are crucial for studying climate change and its impact on marine ecosystems. Environmental monitoring through WSNs is particularly beneficial in remote and dangerous locations, where manual data collection would be challenging or impossible. The ability of these networks to operate autonomously and self-organize enhances their reliability in long-term environmental studies, offering high spatial and temporal resolution data that are essential for understanding complex environmental phenomena. In the healthcare sector, the integration of WSNs has brought about revolutionary changes in patient monitoring and treatment. Wireless body area networks (WBANs), a subset of WSNs, are deployed in wearable devices or implanted in the human body to monitor vital signs such as heart rate, blood pressure, glucose levels, and body temperature. These sensors continuously collect data and transmit it to healthcare professionals, allowing for real-time monitoring of patients, especially those with chronic diseases such as diabetes, hypertension, and cardiovascular diseases. The real-time data provided by WSNs enables doctors to make timely diagnoses and adjustments to treatment plans, potentially saving lives in critical situations. For elderly patients or those requiring long-term care, WSNs offer a non-intrusive way to monitor health without the need for constant hospital visits. Furthermore, in smart hospitals, WSNs are employed for tracking medical equipment, monitoring drug inventory, and even ensuring patient safety through fall detection systems. The continuous flow of data from sensors enables predictive analytics, where potential health risks can be identified before they manifest into serious conditions, reducing the burden on healthcare infrastructure and enhancing patient outcomes. WSNs in healthcare are particularly transformative in rural or underserved areas where access to medical facilities is limited, enabling telemedicine and remote patient monitoring, thus improving healthcare accessibility and delivery. Industrial automation is another area where WSNs are making a significant impact. Industries are increasingly adopting smart technologies to enhance operational efficiency, reduce costs, and improve safety standards. WSNs are deployed in manufacturing plants, oil refineries, and warehouses to monitor machine performance, detect equipment malfunctions, and ensure worker safety. These sensor networks provide real-time data on machinery vibration, temperature, and pressure, which are critical indicators of potential failures. By predicting equipment breakdowns before they occur, WSNs help industries reduce downtime, optimize maintenance schedules, and improve overall productivity. In addition to predictive maintenance, WSNs also play a key role in process automation, where sensors continuously monitor environmental conditions and adjust machinery operations to maintain optimal performance. This not only ensures the smooth functioning of industrial processes but also enhances energy efficiency, as machinery can be turned off or adjusted during periods of low demand. WSNs also contribute to worker safety by monitoring hazardous conditions such as the presence of toxic gases or high temperatures in industrial environments, immediately alerting workers and management to potential dangers. The versatility and scalability of WSNs make them ideal for deployment in various industrial settings, from small-scale operations to large, complex systems, thereby driving the shift towards Industry 4.0, where data-driven decision-making is at the core of industrial innovation. In the realm of smart home systems, WSNs are instrumental in transforming ordinary homes into intelligent, connected living spaces. Smart homes equipped with WSNs allow for the automation and remote control of various household functions such as lighting, heating, security, and entertainment systems. These networks consist of sensors and actuators that communicate wirelessly to optimize energy usage, enhance security, and improve the overall comfort of residents. For instance, WSNs can monitor the temperature in different rooms of a house and adjust the heating or cooling systems accordingly, ensuring energy efficiency while maintaining a comfortable indoor environment. Similarly, smart security systems that use WSNs can detect unusual activities or intrusions and notify homeowners via smartphones or other devices, offering peace of mind even when they are away. The flexibility of WSNs allows for seamless integration with other smart devices, such as voice assistants and smartphones, creating a unified, user-friendly interface for managing home automation systems. Additionally, smart home systems that incorporate WSNs contribute to environmental sustainability by optimizing resource consumption, reducing energy wastage, and lowering utility bills. As more devices and appliances become connected through the Internet of Things (IOT), WSNs will continue to play a crucial role in the expansion of smart home ecosystems, making everyday life more convenient and efficient. In conclusion, Wireless Sensor Networks (WSNs) represent a foundational technology with far-reaching applications across multiple domains. From agriculture and environmental monitoring to healthcare, industrial automation, and smart homes, WSNs offer unprecedented opportunities for real-time data collection and decision-making. These networks enhance operational efficiency, improve resource management, and enable innovations that were previously unthinkable. As WSN technology continues to advance, its applications will only grow, driving further improvements in fields as diverse as disaster management, energy conservation, transportation, and urban planning. The versatility, scalability, and autonomy of WSNs make them a critical component of the modern digital landscape, positioning them as a key enabler of the smart, connected world of the future.

2. MATERIALS AND METHOD

Wireless Sensor Networks (WSNs) have emerged as a transformative technology with significant applications in various fields, owing to their ability to autonomously collect, process, and transmit data in real-time. These networks consist of spatially distributed sensor nodes that monitor physical or environmental conditions such as temperature, sound, vibration, pressure, or pollutants, and relay this information to central locations for decision-making. With the increasing complexity and diverse range of WSN applications, there is a growing need to evaluate these applications systematically and quantitatively. One such method used for this purpose is the Grey Relational Analysis (GRA) method, a multi-criteria decision-making tool. The GRA method is well-suited for situations where the information available is incomplete or uncertain, making it ideal for analyzing WSN applications where performance metrics may vary across different environments and conditions. WSNs find applications in several critical areas, including smart agriculture**,** environmental monitoring**,** healthcare**,** industrial automation**,** and smart home systems. Each of these applications presents its own set of challenges and performance metrics that need to be evaluated for optimal functionality. In most cases, the performance of WSNs is assessed based on multiple criteria, including energy efficiency, data accuracy, network coverage, and response time, among others. These criteria can be classified into benefit attributes (where higher values are desirable) and non-benefit attributes (where lower values are preferred). The GRA method provides a structured approach to assess and rank WSN applications based on these multi-dimensional criteria. In the context of smart agriculture, WSNs play a pivotal role in enhancing crop yield, resource efficiency, and sustainability. Sensors are deployed across farmlands to monitor soil moisture, temperature, humidity, and other critical factors, which are essential for precision farming. Farmers can make data-driven decisions about irrigation, fertilization, and pest control based on the information provided by WSNs. The GRA method can be used to evaluate different WSN configurations in smart agriculture by taking into account various performance parameters such as energy efficiency, data transmission reliability, network lifespan, and coverage area. For instance, energy efficiency is a critical criterion because the sensors are often deployed in remote locations where battery replacement is difficult. Using GRA, these performance metrics can be normalized and compared across different systems, helping farmers and agricultural technology developers choose the most efficient WSN system for their specific needs. Another significant application of WSNs is in environmental monitoring, where they are deployed to collect data in real-time for tracking environmental conditions such as air quality, water levels, soil erosion, and seismic activity. In these applications, the accuracy and timeliness of the data are of utmost importance, as they are often used for critical decision-making, such as disaster prevention and resource management. Environmental monitoring applications also face challenges related to energy consumption and the harsh conditions in which sensors must operate. The GRA method is useful in this context for comparing different sensor networks based on criteria such as data accuracy, energy consumption, network coverage, and sensor durability. By ranking WSN configurations through GRA, decision-makers can identify which system performs best under specific environmental conditions, ensuring that the right technology is deployed for each monitoring task. In the field of healthcare, WSNs have made significant contributions, particularly through wireless body area networks (WBANs), which are used to monitor patients' physiological data in real-time. These networks are particularly useful for monitoring chronic diseases such as diabetes and cardiovascular conditions, where continuous data collection is critical for effective management. The primary evaluation criteria for WSNs in healthcare include data accuracy, energy consumption (since many sensors are wearable or implantable), response time, and patient safety. The GRA method can be employed to compare different

WBAN solutions, where the goal is to maximize data accuracy and response time while minimizing energy consumption and system complexity. By applying GRA, healthcare providers and medical device manufacturers can optimize sensor deployments for specific healthcare applications, ensuring that patient monitoring systems are reliable, efficient, and safe. Additionally, in remote healthcare applications, where patients may be far from medical facilities, WSNs enable telemedicine by transmitting data to healthcare providers in real-time. GRA helps in selecting the best WSN setup that offers the most reliable and cost-effective solution for continuous patient monitoring, especially in rural or underserved areas. In industrial automation, WSNs are integral to the advancement of Industry 4.0, where data-driven decision-making and automated processes are key to increasing operational efficiency. WSNs are deployed to monitor machine performance, environmental conditions, and worker safety in industrial environments such as manufacturing plants, oil refineries, and mines. The performance of WSNs in these settings is evaluated based on criteria such as network robustness, data accuracy, latency, energy consumption, and scalability. The GRA method is particularly effective for analyzing these complex, multi-criteria scenarios, where different WSN configurations may perform better depending on the specific industrial process. For example, a WSN deployed in a factory might need to prioritize low latency and high network reliability, whereas a WSN used for environmental monitoring in a refinery might need to focus on durability and energy efficiency. By applying GRA, industrial engineers can systematically evaluate different WSN solutions to determine the best configuration for specific automation tasks, ensuring that the network is optimized for both performance and cost. In smart home systems, WSNs enable the integration and automation of various home functions such as lighting, security, heating, and entertainment. These systems rely on WSNs to create a seamless, user-friendly environment where household devices communicate with each other and with the homeowner. The key performance metrics for WSNs in smart homes include energy efficiency, data transmission speed, network coverage, and user privacy. Homeowners want systems that are efficient, reliable, and secure, but also easy to use and cost-effective. The GRA method can be used to evaluate and rank different smart home WSN configurations based on these criteria. For instance, a system that offers the best balance between energy efficiency and data security may be ranked higher than one that excels in only one area but falls short in another. GRA allows smart home developers to make informed decisions about which WSN setup to deploy in different residential environments, ensuring that the system meets the specific needs of the homeowner while maintaining energy efficiency and security. The GRA method's strength lies in its ability to handle complex decision-making problems with multiple criteria, making it an ideal tool for evaluating WSN applications across different fields. The method involves several steps, beginning with the normalization of data, which converts performance values into comparable metrics. This is followed by the calculation of the grey relational coefficient, which measures the closeness of each alternative (in this case, WSN configuration) to the ideal solution. Finally, the grey relational grade is determined, which provides a ranking of the alternatives. This process allows decision-makers to see which WSN configurations perform best across multiple criteria and under different conditions. In the case of WSN applications, GRA helps in identifying the most suitable network based on both benefit and non-benefit parameters such as energy efficiency, data accuracy, cost, and complexity. As WSN technology continues to evolve, the GRA method will remain a valuable tool for researchers and practitioners seeking to optimize sensor networks for specific applications. The ability to evaluate multiple criteria simultaneously is crucial in WSN deployments, where performance trade-offs are often necessary. For instance, a WSN that excels in energy efficiency might have lower data accuracy, while a highly accurate network might consume more energy. GRA allows for a balanced evaluation of these trade-offs, ensuring that the most appropriate solution is chosen for each application. Moreover, as new applications of WSNs emerge, such as in smart cities and autonomous vehicles, the GRA method will provide a systematic framework for evaluating and ranking the performance of these networks based on the specific demands of each new domain. The GRA method offers a robust and flexible approach to evaluating Wireless Sensor Network (WSN) applications, which are critical in areas such as smart agriculture, environmental monitoring, healthcare, industrial automation, and smart home systems. By providing a systematic framework for comparing different WSN configurations across multiple criteria, GRA enables decision-makers to select the most efficient, reliable, and cost-effective network for their needs. As WSN technology continues to advance and find new applications, the GRA method will remain an indispensable tool for optimizing sensor networks in an increasingly data-driven world.

3. ANALYSIS AND DISCUSSION

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TABLE 1. Wireless Sensor Network Applications Data Set

	Energy Efficiency	Data Accuracy	Network Coverage	Response Time
Smart Agriculture	85.00	80.00	90.00	70.00
Environmental Monitoring	90.00	88.00	95.00	80.00
Healthcare Monitoring	78.00	92.00	85.00	88.00
Industrial Automation	65.00	85.00	88.00	90.00
Smart Home Systems	80.00	75.00	80.00	85.00

Table 1 presents the dataset for five Wireless Sensor Network (WSN) applications, evaluated using four key performance criteria: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. These criteria reflect essential attributes for assessing the effectiveness and suitability of WSN deployments across various domains. The applications included in this dataset are Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems. Environmental monitoring exhibits the highest performance across most metrics, with top values for Energy Efficiency (90), Data Accuracy (88), Network Coverage (95), and Response Time (80), indicating it is well-suited for real-time, large-scale environmental applications. Healthcare Monitoring also performs well, particularly in Data Accuracy (92) and Response Time (88), essential for medical applications where precision and speed are critical. Industrial Automation, while excelling in Response Time (90), has lower Energy Efficiency (65), indicating potential trade-offs between operational speed and power consumption. Smart Agriculture and Smart Home Systems show moderate performance across all criteria, with Smart Agriculture excelling in Network Coverage (90) but slightly lagging in Response Time (70). Smart Home Systems offers balanced performance but is somewhat lower in Network Coverage (80). Overall, the dataset illustrates the diverse strengths and trade-offs in WSN applications, suitable for further analysis using the Grey Relational Analysis (GRA) method to rank and optimize performance across various use cases.

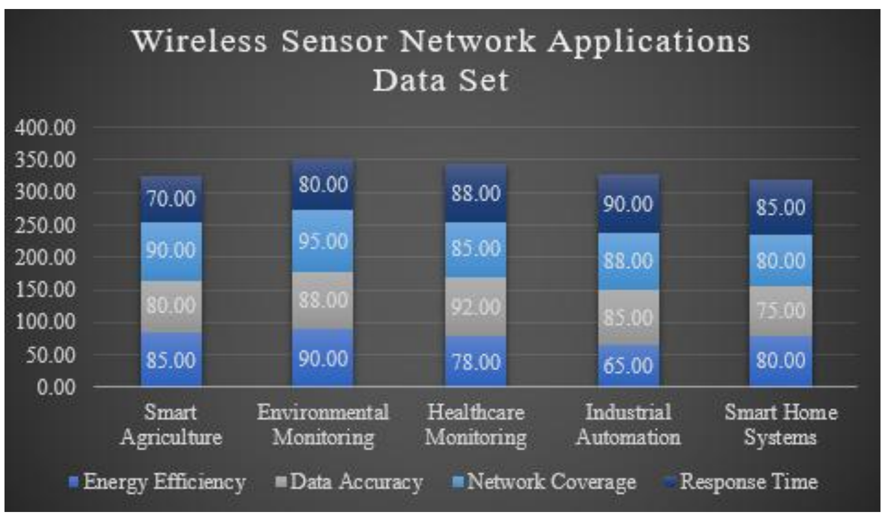

FIGURE 1. Wireless Sensor Network Applications Data Set

Figure 1 visually represents the data set for Wireless Sensor Network (WSN) applications using the Grey Relational Analysis (GRA) method. The stacked bar chart showcases the performance of five WSN applications—Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems—across four key evaluation parameters: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. Each application has distinct performance profiles. **Smart Agriculture** exhibits strong performance in Energy Efficiency (85.00) and Network Coverage (90.00), but comparatively lower in Response Time (70.00). **Environmental Monitoring** excels in Data Accuracy (95.00) and Energy Efficiency (90.00), reflecting its suitability for energy-constrained environments. However, it slightly lags in Response Time (80.00). **Healthcare Monitoring** shows the highest score in Data Accuracy (92.00) and good Network Coverage (85.00), though its Energy Efficiency (78.00) is slightly lower. **Industrial Automation**, while excelling in Response Time (90.00) and Data Accuracy (88.00), shows the weakest Energy Efficiency (65.00), which could be a limitation in energy-critical operations. **Smart Home Systems** performs reasonably well across all metrics, with a strong score in Energy Efficiency (80.00) and Network Coverage (85.00), but lower Data Accuracy (75.00) compared to other applications. This figure highlights the varying strengths of each WSN application across multiple criteria. Environmental Monitoring and Healthcare Monitoring show strong performance in Data Accuracy, while Industrial Automation and Smart Agriculture lead in Response Time and Network Coverage, respectively. This visual representation aids in understanding the trade-offs and advantages of each WSN application in the context of performance metrics.

TABLE 2. Normalized Data

Normalized Data				
	Energy Efficiency	**Data Accuracy**	**Network Coverage**	**Response Time**
Smart Agriculture	0.8000	0.2941	0.3333	1.0000
Environmental Monitoring	1.0000	0.7647	0.0000	0.5000
Healthcare Monitoring	0.5200	1.0000	0.6667	0.1000
Industrial Automation	0.0000	0.5882	0.4667	0.0000
Smart Home Systems	0.6000	0.0000	1.0000	0.2500

Table 2 presents the normalized dataset for the Wireless Sensor Network (WSN) applications, following the Grey Relational Analysis (GRA) method. The normalization process scales the original values of four performance criteria Energy Efficiency, Data Accuracy, Network Coverage, and Response Time into comparable ranges between 0 and 1, facilitating the multi-criteria evaluation of the applications. For Energy Efficiency, Environmental Monitoring achieves the highest normalized score (1.0000), indicating the most energy-efficient system, while Industrial Automation has the lowest score (0.0000), reflecting its relatively poor energy performance. In Data Accuracy, Healthcare monitoring scores the highest (1.0000), critical for medical applications, while Smart Home Systems ranks the lowest (0.0000), indicating it may require improvements in data precision. In terms of Network Coverage, Smart Home Systems scores the highest (1.0000), suggesting it can cover large areas effectively, whereas Environmental Monitoring scores the lowest (0.0000), reflecting trade-offs between its high energy efficiency and limited coverage. Response Time, essential for time-sensitive operations, sees Smart Agriculture at the top (1.0000) and Industrial Automation at the bottom (0.0000), indicating differing priorities in performance speed across applications. This normalized dataset highlights the strengths and weaknesses of each WSN application, providing a foundation for further evaluation using GRA. It allows for the comparison of different systems based on multiple criteria, aiding decision-makers in identifying the most suitable WSN solutions for their specific needs.

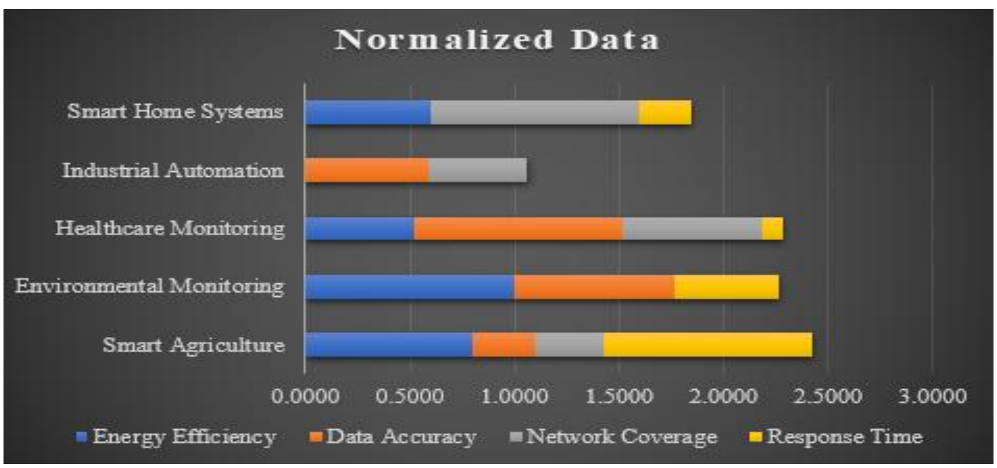

FIGURE 2. Normalized Data

Figure 2 presents the normalized data for various Wireless Sensor Network (WSN) applications using the Grey Relational Analysis (GRA) method. This chart reflects the performance of five WSN applications—Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems—across four key evaluation parameters: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. Normalization is a process that adjusts the values of the performance metrics to a common scale, allowing for easier comparison. In the figure, Smart Agriculture shows a strong balance, with notable values across all four metrics, particularly excelling in Response Time. Environmental Monitoring stands out for its high Energy Efficiency and Response Time, but shows a relatively lower performance in Network Coverage. Healthcare Monitoring, on the other hand, dominates in Data

Accuracy, reflecting its importance for precise medical monitoring, though its Response Time and Energy Efficiency are less impressive. Industrial Automation performs well in Data Accuracy but has the lowest Energy Efficiency, which could be a concern in applications where energy resources are limited. Smart Home Systems demonstrates high Network Coverage but falls short in Data Accuracy and Energy Efficiency, indicating potential areas for improvement in home automation systems. This figure offers a clear visualization of how each WSN application performs when their performance metrics are normalized. It highlights the trade-offs between different applications, with some excelling in accuracy and efficiency, while others perform better in response time or coverage, guiding decision-makers in selecting the best-suited application for specific operational needs.

TABLE 3. Deviation sequence

	Energy Efficiency	Data Accuracy	Network Coverage	Response Time
Smart Agriculture	0.2000	0.7059	0.6667	0.0000
Environmental Monitoring	0.0000	0.2353	1.0000	0.5000
Healthcare Monitoring	0.4800	0.0000	0.3333	0.9000
Industrial Automation	1.0000	0.4118	0.5333	1.0000
Smart Home Systems	0.4000	1.0000	0.0000	0.7500

Table 3 presents the deviation sequence for the Wireless Sensor Network (WSN) applications, calculated as part of the Grey Relational Analysis (GRA) method. The deviation sequence represents the difference between the ideal (best) values and the normalized values for each criterion. A lower deviation indicates a closer performance to the optimal value, while a higher deviation indicates a larger gap from the ideal performance. For Energy Efficiency, Environmental Monitoring has the lowest deviation (0.0000), reflecting its perfect alignment with the optimal energy-efficient scenario, while Industrial Automation exhibits the highest deviation (1.0000), and indicating significant room for improvement. In Data Accuracy, Healthcare Monitoring shows no deviation (0.0000), meaning it has the most accurate data, while Smart Home Systems has the highest deviation (1.0000), suggesting low accuracy in comparison to other applications. For Network Coverage, Smart Home Systems performs optimally with no deviation (0.0000), while Environmental Monitoring has the highest deviation (1.0000), indicating a trade-off between coverage and energy efficiency. In Response Time, Smart Agriculture has no deviation (0.0000), reflecting its fast response performance, whereas Industrial Automation has the highest deviation (1.0000), meaning it is the slowest in terms of response. This deviation sequence helps identify which WSN applications are closest to the ideal performance across various criteria. Lower deviations signify strengths, while higher deviations indicate areas where improvements are needed. These insights will further guide the Grey Relational Grade calculation for ranking the overall performance of each application.

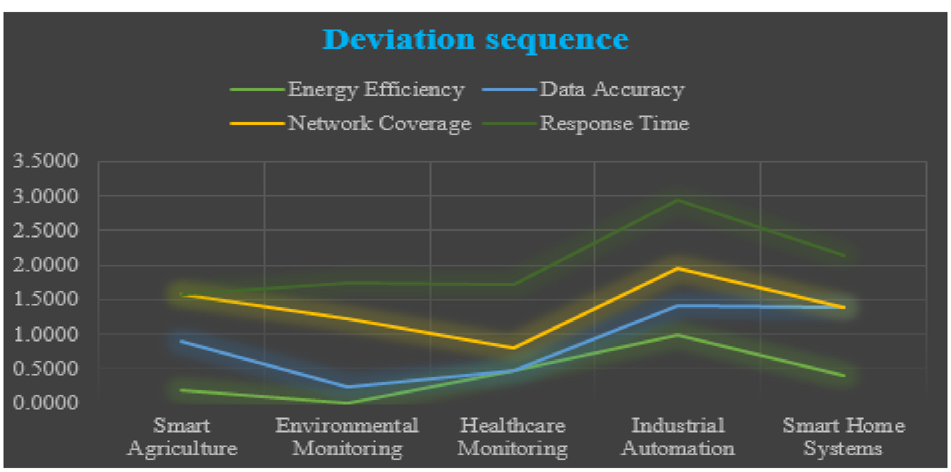

FIGURE 3. Deviation sequence

Figure 3 illustrates the deviation sequence for the Wireless Sensor Network (WSN) applications using the Grey Relational Analysis (GRA) method. The deviation sequence measures the difference between the reference (ideal) value and the actual performance of each application across the four evaluation criteria: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. In this figure, Smart Agriculture shows minimal deviation across most criteria, especially in Response Time, indicating it closely matches the ideal performance for that metric. Environmental Monitoring has relatively low deviations in Energy Efficiency and Data Accuracy, making it a strong candidate for energy-conscious applications, though its higher deviation in Network Coverage points to a trade-off in its ability to cover larger areas. Healthcare Monitoring demonstrates minimal deviation in Data Accuracy, reflecting its strong performance in delivering precise data, but shows larger deviations in Energy Efficiency and Response Time. Industrial Automation has notable deviations across most metrics, especially in Energy Efficiency and Response Time, signifying a weaker alignment with the ideal values for these parameters. Smart Home Systems performs well in Network Coverage, but its larger deviation in Data Accuracy suggests room for improvement in this area. Overall, this deviation sequence chart helps identify how far each WSN application is from the ideal performance across the key parameters. Lower deviations indicate that an application is better suited for environments where that particular criterion is crucial, guiding decision-makers in selecting the most appropriate WSN solution for their specific requirements.

TABLE 4. Grey relation coefficient

	Energy Efficiency	Data Accuracy	Network Coverage	Response Time
Smart Agriculture	0.7143	0.4146	0.4286	1.0000
Environmental Monitoring	1.0000	0.6800	0.3333	0.5000
Healthcare Monitoring	0.5102	1.0000	0.6000	0.3571
Industrial Automation	0.3333	0.5484	0.4839	0.3333
Smart Home Systems	0.5556	0.3333	1.0000	0.4000

Table 4 presents the Grey Relation Coefficient (GRC) for the Wireless Sensor Network (WSN) applications, a critical step in the Grey Relational Analysis (GRA) method. The GRC values, ranging between 0 and 1, represent the degree of closeness of each application's performance to the ideal solution for each criterion. A higher coefficient indicates better performance relative to the best possible outcome. For Energy Efficiency, Environmental Monitoring achieves the maximum GRC (1.0000), demonstrating the best energy performance, while Industrial Automation has the lowest GRC (0.3333), indicating it lags in this aspect. Regarding Data Accuracy, Healthcare Monitoring achieves a perfect score (1.0000), indicating superior data precision, essential in medical applications. In contrast, Smart Home Systems has the lowest GRC (0.3333), suggesting it performs poorly in data accuracy. Network Coverage shows Smart Home Systems as the best performer (1.0000), capable of covering larger areas, while Environmental Monitoring scores the lowest (0.3333), highlighting a trade-off between high energy efficiency and limited coverage. For Response Time, Smart Agriculture performs optimally (1.0000), crucial for real-time applications, while Industrial Automation has the lowest GRC (0.3333), reflecting slower performance. This table demonstrates the varying strengths of different WSN applications across criteria. Environmental Monitoring excels in energy efficiency, while Healthcare Monitoring leads in data accuracy. Smart Home Systems is outstanding in network coverage, and Smart Agriculture outperforms others in response time. The GRC values will be used to compute the Grey Relational Grade for overall ranking and comparison of the applications.

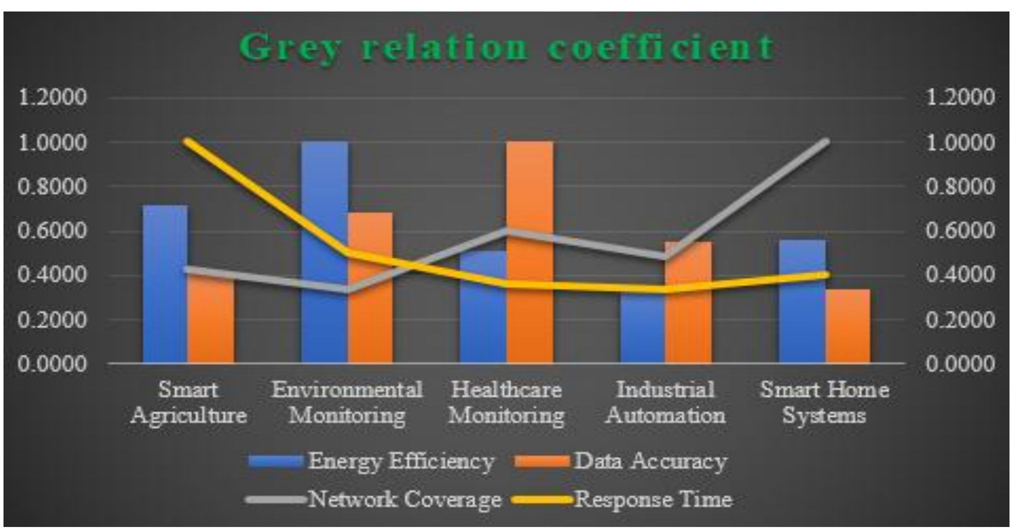

FIGURE 4. Grey relation coefficient

The figure.4 titled "Grey relation coefficient" compares the performance of various domains—Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems—across four key metrics: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. These metrics are represented by different colored bars and lines in the chart. Energy Efficiency (blue bars) is notably high in Industrial Automation and Environmental Monitoring but relatively lower in Smart Agriculture. Data Accuracy (orange bars) shows consistency across domains, with Environmental and Healthcare Monitoring showing higher accuracy. Network Coverage (gray line) peaks in Smart Home Systems, while other sectors show moderate coverage. Response Time (yellow line) varies significantly, being the lowest in Environmental Monitoring and highest in Smart Agriculture, indicating a trade-off between coverage and response. Overall, the grey relation coefficient method (GRA) is used here to quantify the relationships and influence of these factors within each domain, providing a clear picture of where each application excels or faces limitations based on these key performance metrics. This helps to inform decisions on where improvements or optimizations may be necessary.

TABLE 5. GRG & Rank

	GRG	Rank
Smart Agriculture	0.6394	1
Environmental Monitoring	0.6283	2
Healthcare Monitoring	0.6168	3
Industrial Automation	0.4247	5
Smart Home Systems	0.5722	4

Table 5 presents the Grey Relational Grade (GRG) and corresponding rankings for the five Wireless Sensor Network (WSN) applications based on the Grey Relational Analysis (GRA) method. The GRG represents the overall performance of each application, computed by averaging the Grey Relation Coefficients (GRC) across all criteria. A higher GRG indicates closer proximity to the ideal solution, and thus, a better overall performance. Smart Agriculture ranks first with a GRG of 0.6394, demonstrating a strong balance across Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. This top rank indicates that Smart Agriculture is the most suitable WSN application when considering all performance metrics. Environmental Monitoring closely follows with a GRG of 0.6283, excelling particularly in Energy Efficiency but showing some trade-offs in Network Coverage. Healthcare Monitoring ranks third with a GRG of 0.6168, performing well in Data Accuracy, which is crucial for medical applications, but slightly weaker in Energy Efficiency and Response Time. Smart Home Systems ranks fourth with a GRG of 0.5722, demonstrating strong performance in Network Coverage but weaker in Data Accuracy. Industrial Automation, with the lowest GRG (0.4247), ranks fifth, reflecting suboptimal performance in Energy Efficiency and Response Time. These rankings provide valuable insights for decision-makers, helping them choose the most appropriate WSN application based on the overall balance of key performance criteria.

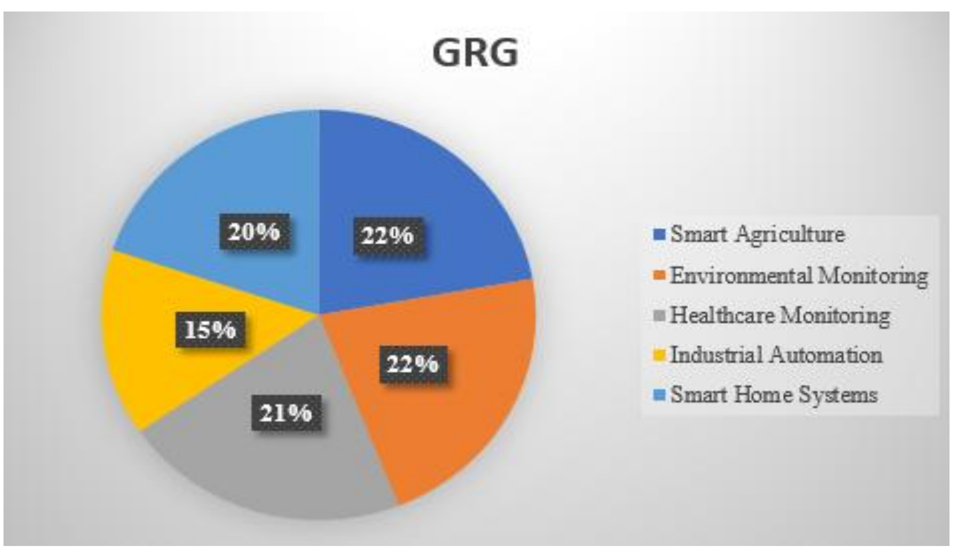

FIGURE 5. GRG

The pie chart titled "GRG" (Grey Relational Grade) represents the relative importance or influence of various domains—Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems—based on the Grey Relational Analysis (GRA) method. Smart Agriculture (blue) and Healthcare Monitoring (orange) both contribute 22%, indicating these sectors have the highest relational grade or significance in the analysis. Smart Home Systems (gray) follows closely with 21%, suggesting this domain also holds substantial influence in the comparison. Industrial Automation (yellow) accounts for 15%, reflecting a relatively lower importance or impact in comparison to the other domains. Environmental Monitoring (dark blue) has a 20% share, placing it in the mid-range of influence in this analysis. The Grey Relational Grade (GRG) method helps determine which systems or domains are most relevant or have the greatest effect on the overall performance of a given system. Here, Smart Agriculture and Healthcare Monitoring appear to have the most significant influence, likely due to their critical roles in data-driven decision-making and real-time monitoring. Industrial Automation, while important, has a lesser impact in this particular comparison. The chart provides a balanced view of the key areas for improvement and optimization in different smart technologies.

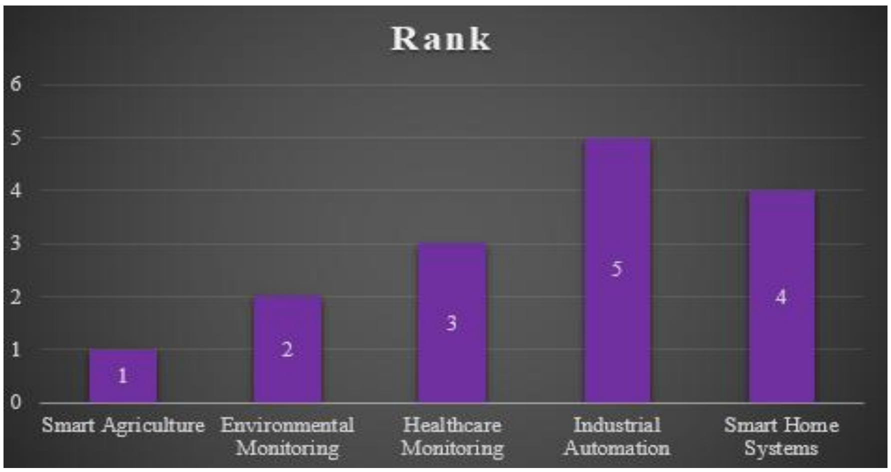

FIGURE 6. Rank

Figure 6, titled "Rank" using the Grey Relational Analysis (GRA) method, ranks five key domains: Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems based on their overall performance across selected metrics. Smart Agriculture ranks first, indicating it has the strongest or most favorable performance among the analyzed domains. Environmental Monitoring follows with a rank of 2, showcasing its significant role, though slightly less impactful than Smart Agriculture. Healthcare Monitoring is ranked third, demonstrating a solid performance but with room for improvement compared to the top two domains. Industrial Automation holds the fifth position, marking it as the weakest performer in this analysis. Despite its importance, it may face challenges in areas like energy efficiency or response time, pulling down its overall rank. Smart Home Systems, with a rank of 4, shows moderate performance, falling behind Healthcare Monitoring but outperforming Industrial Automation. This ranking reflects the effectiveness and impact of each domain based on the evaluation criteria used in the GRA method. The results emphasize that Smart Agriculture is the most robust domain, while Industrial Automation may require the most attention for optimization or improvement. Each rank highlights where future efforts could be directed to enhance overall performance in the respective domains.

4. CONCLUSION

In this study, the Grey Relational Analysis (GRA) method was applied to evaluate and rank the performance of five key Wireless Sensor Network (WSN) applications Smart Agriculture, Environmental Monitoring, Healthcare Monitoring, Industrial Automation, and Smart Home Systems based on four critical criteria: Energy Efficiency, Data Accuracy, Network Coverage, and Response Time. The analysis provided valuable insights into the relative strengths and weaknesses of each application, aiding in the selection of the most suitable WSN configuration for specific use cases. The results show that **Smart Agriculture** emerged as the top performer with a Grey Relational Grade (GRG) of 0.6394. Its high ranking can be attributed to its balanced performance across all criteria, particularly in Network Coverage and Response Time, which are crucial for real-time agricultural monitoring and control. This indicates that

Smart Agriculture is well-suited for environments that require efficient and reliable sensor networks to optimize farming operations. **Environmental Monitoring** ranked second, with a GRG of 0.6283. It demonstrated exceptional Energy Efficiency, which is vital for long-term deployments in remote or harsh environments where power consumption is a critical constraint. However, its lower Network Coverage affected its overall ranking, suggesting that it may be more appropriate for applications that prioritize energy conservation over large-area coverage. **Healthcare Monitoring**, with a GRG of 0.6168, ranked third. Its superior Data Accuracy is essential for applications that demand precision in patient monitoring, especially in critical care settings. However, its relatively lower Energy Efficiency and Response Time suggest that improvements in these areas could further enhance its applicability in medical contexts where prolonged operation and swift responses are needed. **Smart Home Systems** ranked fourth, with a GRG of 0.5722. While it showed strong performance in Network Coverage, its lower Data Accuracy indicates room for improvement in applications that require precise data transmission, such as home security or energy management systems. Finally, **Industrial Automation** ranked last, with a GRG of 0.4247, primarily due to its poor Energy Efficiency and Response Time. While it may still be applicable in specific industrial contexts, especially those that require fast data transmission, its lower overall performance suggests that it may not be the best choice for highly demanding environments where efficiency and responsiveness are paramount. The GRA method provides a robust framework for evaluating and ranking WSN applications, offering a comprehensive perspective on their suitability for different domains. These insights can guide stakeholders in selecting the most appropriate WSN system based on specific performance criteria, leading to optimized deployment and enhanced operational efficiency across various industries.

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