Power System Technology
ISSN:1000-3673

Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

A Framework for Designing WSNs Using Dynamic Programming for Better Performance

Smt. Chaya K, Dr. Shylaja B S

Department of Computer Science and Engineering, GEC, Chamarajanagara, research scholar, Dr. AIT, chayakraj@gmail.com, ORCID: 0009-0004-8290-0703

Professor, Department of information science, Dr. A. I. T, Bengaluru, ORCID: 0000-0003-0332-1734

Abstract: - Wireless Sensor Networks (WSNs) are essential for many applications, including smart cities, industrial automation, and environmental monitoring. However, maximizing the durability and performance of these networks is a major problem because of the limitations on processing power and battery life. To enhance routing effectiveness, energy management, and overall network performance, this research proposes a methodology for constructing WSNs utilizing dynamic programming.

The suggested architecture balances network demand and minimizes energy consumption by optimizing routing decisions using dynamic programming techniques. The model finds the best routes for data transmission by considering energy levels, traffic patterns, and real-time sensor conditions. This ensures dependable communication with little energy overhead. For adaptive sleep-wake scheduling, the framework also incorporates an Artificial Neural Network (ANN), which enables sensor nodes to switch to low-power modes during idle times while preserving network responsiveness.

The framework also includes cluster creation and management algorithms, which group sensor nodes according to proximity and energy levels to improve scalability and efficiency. By further minimizing duplicate transmissions, data aggregation techniques enhance overall energy efficiency. Extensive simulations used to evaluate performance show that, in comparison to conventional methods, the suggested architecture greatly increases the network's operational lifetime while enhancing throughput, latency, and fault tolerance.

According to experimental findings, integrating machine learning methods with dynamic programming improves WSN decision-making, resulting in more efficient resource allocation and energy saving. ANN-based models' capacity to adapt to changing network circumstances is ensured by their integration with routing and sleep scheduling systems. In order to better optimize the framework for large-scale WSN deployments, future research will concentrate on integrating reinforcement learning.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Keywords: *Wireless Sensor Networks, Dynamic Programming, Energy Efficiency, Routing Optimization, Sleep-Wake Scheduling, Artificial Neural Networks*

1. Introduction

Wireless Sensor Networks (WSNs) have become extremely important for number of applications, such as smart cities, industrial automation, and environmental monitoring. These networks are made up of many low-power sensor nodes that wirelessly gather and send data to a base station for processing. However, the limited battery capacity of sensor nodes and their deployment in distant or inaccessible settings provide significant hurdles for WSNs in terms of energy economy, data routing, and network lifetime. Reliable data transmission and extended network operation depend on effective resource management and optimization strategies.

Ineffective energy use and a shorter network lifetime result from traditional routing and energy management techniques' frequent inability to dynamically adjust to shifting network conditions. By decomposing difficult decision-making issues into smaller subproblems and recursively solving them, dynamic programming provides a potent optimization method to overcome these difficulties. Routing pathways may be adjusted to decrease energy consumption, reduce packet loss, and enhance overall network efficiency in WSNs with dynamic programming.

To further improve energy efficiency, this system combines dynamic programming with a sleep-wake scheduling mechanism based on Artificial Neural Networks (ANN). Adaptive decision-making for sensor activation and data transmission is made possible by the ANN model's real-time network condition prediction. Cluster creation techniques are also used to manage network strain and minimize duplicate data transfers.

This study investigates how WSN performance may be greatly improved by using dynamic programming, machine learning, and clustering approaches. The suggested method makes WSNs more resilient and sustainable for practical uses by guaranteeing optimum routing, effective energy use, and extended network lifetime.

2. Literature Survey

Research on wireless sensor networks (WSNs) [1] with energy constraints focuses on extending network lifetime while preserving peak performance. To address these issues, Wendong Xiao and Ruizhuo Song suggest a sensor scheduling strategy based on adaptive dynamic programming (ADP). To ensure estimation accuracy and minimize energy consumption, their study formulates the problem as an infinite-step restricted optimum control problem using Kalman filter (KF) prediction.

Current strategies for energy-efficient WSNs may be generally divided into two categories: modifying the sensing or transmission range and scheduling sensor nodes between active and

Power System Technology
ISSN:1000-3673

Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

sleep modes. Heinzelman et al. (2002) was one of the first to offer architecture-specific protocols for sensor networks. To overcome the "curse of dimensionality," as Bellman (1957) defined it, more sophisticated approaches used dynamic programming techniques. ADP techniques, which include Q-learning and heuristic dynamic programming, are renowned for their real-time implementation and computational efficiency.

The suggested approach creatively approximates the expected performance index using neural networks and an iterative ADP algorithm. In addition to guaranteeing the convergence of performance indices, this strategy offers a verifiable way to accomplish ideal scheduling while dealing with energy limitations. It is consistent with the use of ADP in complicated control systems by Zhang et al. (2008) and Liu et al. (2005).

By showing increased estimation accuracy and longer network lifetime, the study's simulation confirms its technique. While adjusting to dynamic changes in the environment, the KF-based state estimation makes sure the system stays below predetermined error levels. Through the integration of real-time sensor scheduling and neural network-based ADP, this framework makes a substantial contribution to WSN research.

The paper Backtracking-based dynamic programming for resolving transmit ambiguities in WSN localization discusses the difficulties of localizing sensor agents in situations when resource limitations make unique identification either impractical or impossible. [2] Schlupkothen et al. present a dynamic programming approach that uses backtracking to address transmission ambiguities in WSN localization. Their work focuses on situations where tiny sensors must locate effectively under hardware and energy limits but lack unique identifiers, such as oil field exploration and groundwater monitoring.

In WSNs, localization frequently depends on sensor range measurements. These measurements create ambiguity in the lack of unique IDs, which presents serious optimization problems. Current methods, such models for integer linear programming (ILP), need a lot of computing power. To effectively address these uncertainties, this paper proposes a maximum a posteriori (MAP)-optimal method utilizing dynamic programming and graph decomposition.

To graphically depict the transmit ambiguity problem, the suggested approach provides k-ambiguity trees. By taking advantage of graph structures' fixed-parameter tractability, the approach streamlines the optimization process and reduces runtime by up to 88.5% when compared to conventional ILP techniques. Backtracking is also used into the method to increase the effectiveness of dynamic programming solutions.

A thorough explanation of the transmit ambiguity resolution problem (TARP), the creation of k-ambiguity trees for structured graph representation, and the use of backtracking to maximize computer efficiency are some of the main contributions. For situations with transmission

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

ambiguity, these developments re-enable traditional localization strategies such as least-squares techniques and semidefinite programming.

The paper A Dynamic Programming Approach for QoS-Aware Power Management in Wireless Video Sensor Networks explains the capacity of Wireless Video Sensor Networks (WVSNs) to record and send video data in contexts with limited resources has drawn a lot of interest. Optimizing power usage while maintaining [3] Quality of Service (QoS) in video transmission is a major difficulty in WVSNs. The literature has put out a few strategies to deal with this problem.

To increase the energy efficiency of wireless sensor networks, dynamic power management (DPM) approaches have been extensively researched. For bursty traffic, such as video, traditional fixed duty cycle solutions are ineffective. Low-power wakeup radios, MAC protocol changes for energy conservation, and dynamic voltage scaling for multimedia processing are some more options Nevertheless, QoS limitations in video transmission are not fully considered by these techniques.

These models have been expanded in recent studies to include multirate transmission across fading channels and realistic video traffic patterns. Markov chains have been used in studies to describe scene transitions and queue dynamics in power management frameworks based on MPEG-coded video sources. These methods use finite-state Markov chains to simulate adaptive modulation coding and wireless channel fluctuations.

The research highlights the necessity of cross-layer power management solutions that are integrated and take into account queueing behavior, channel conditions, and traffic characteristics. Future research should concentrate on the scalability and real-time deployment of MDP-based power management frameworks in extensive WVSNs.

The paper A Dynamic Programming Approach for QoS-Aware Power Management in Wireless Video Sensor Networks, use of wireless sensor networks [4] (WSNs) in industrial automation, environmental monitoring, and surveillance has drawn a lot of interest. Energy efficiency is a major issue in WSNs since sensor nodes have limited resources and are challenging to recharge. To increase network lifespan while preserving connection and data delivery dependability, recent research has concentrated on improving routing techniques and transmission range changes.

Conventional multi-hop routing makes the assumption that every node has a fixed transmission range. Nonetheless, research shows that permitting different transmission ranges may greatly improve energy efficiency. Less nodes stay active due to dynamic transmission power adjustment, which lowers the energy consumption of idle listening. However, maximizing transmission range necessitates striking a balance between higher transmission power and energy savings.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Numerous algorithms have been put forth to tackle this problem. The network is divided into grids using Geographic Adaptive Fidelity (GAF) [4], which assigns active route nodes to each grid. Iterative algorithms were used in other research to optimize transmission distances and reduce energy usage. Nevertheless, these models frequently overlook practical limitations like random deployment and fluctuating traffic demands and assume evenly dispersed nodes.

WSN optimization has made extensive use of dynamic programming algorithms (DPA). This study's method uses DPA to choose the best route nodes and modify their transmission ranges while taking relay node energy and sensor node transmission costs into account. According to simulation data, DPA considerably lowers overall energy usage when compared to iterative algorithms and conventional fixed-range techniques.

3. Methodology

With the purpose of optimizing performance, namely in energy management, routing, and network durability, this study offers a framework for creating Wireless Sensor Networks (WSNs) using dynamic programming. System modeling, data collecting, dynamic programming-based routing optimization, sleep-wake scheduling, and performance evaluation are some of the main steps in the process.

1. System Modelling and Problem Formulation

Sensor nodes that are dispersed geographically and gather and send data to a base station make up the WSN paradigm. The system is defined by the following parameters:

- Network Topology: Sensor node placement can be either organized or random.
- Energy Restrictions: Nodes run on a limited amount of battery power.
- Communication Model: Energy-saving multi-hop data transfer.
- Performance metrics: include latency, energy use, network longevity, and packet delivery ratio (PDR).

The goal is to use dynamic programming to optimize sensor duty cycles and routing patterns to improve energy economy while preserving network dependability.

2. Data Collection and Preprocessing

Environmental variables including temperature, humidity, and energy levels are continually monitored by sensor nodes. The information gathered is subjected to:

- Eliminating inaccurate readings is known as noise filtering.
- Feature extraction involves choosing important indicators that impact network performance, such as connection quality, hop count, and residual energy.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

- Normalization is the process of standardizing variables to guarantee uniformity throughout model training.

3. **Dynamic Programming-Based Routing Optimization**

By reducing energy usage and maintaining data dependability, dynamic programming is used to improve routing decisions. The following is the structure of the routing problem:

$$C(n) = \min_{i \in N} \left[E_{tx}(n,i) + C(i)\right]$$

- State Definition: Energy level, proximity to base station, and available neighbors of each node.

- Recursive Optimization Function:
- The cost at node n is represented by $C(n)$, the energy needed to send data to node i is represented by Etx (n, i), and the set of surrounding nodes is N.
- Backtracking Strategy: Nodes dynamically choose the best routing path based on calculated cost values.

4. **Sleep-Wake Scheduling Using ANN**

To further improve energy efficiency, an Artificial Neural Network (ANN)-based sleep-wake mechanism is incorporated. The model predicts optimal sleep durations for sensor nodes based on:

- Historical Energy Consumption Data
- Traffic Patterns
- Network Load

Using real-world WSN datasets and supervised learning approaches, the ANN is trained. When nodes are not actively sending data, they switch to low-power modes, which prolongs the life of the network.

5. **Cluster Formation and Load Balancing**

The dynamic programming paradigm helps prevent critical components from failing too soon by dividing energy consumption evenly among nodes.

- Residual Energy
- Proximity to Neighboring Nodes
- Communication Efficiency

By distributing energy consumption evenly among nodes, the dynamic programming paradigm helps to avoid crucial components failing too soon.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

6. Performance Evaluation and Comparison

NS-3 is used to evaluate the suggested framework in a simulated WSN environment. Among the key performance indicators are:

- Network Lifetime: Duration until the first node failure.
- Energy Consumption: Total energy utilized by the network.
- Packet Delivery Ratio (PDR): Percentage of successfully transmitted packets.
- Latency: Average time for data to reach the base station.

To verify advantages in energy efficiency and network sustainability, a comparative analysis is conducted against conventional routing protocols like LEACH and AODV.

4. Experimentation and Results

Experiment Setup

Simulation Parameters

The experiment was conducted using the **NS-3** network simulator. The key parameters used in the simulation are:

Parameter	Value
Number of Nodes	100
Simulation Area	1000m × 1000m
Transmission Range	100m
Initial Energy per Node	2 Joules
Packet Size	512 bytes
Routing Protocols	Dynamic Programming, AODV, LEACH
Simulation Time	1000 seconds

Performance Metrics

The evaluation considers the following performance metrics:

- Energy Consumption (E_{total}): Total energy used by all sensor nodes.
- Network Lifetime (T_{life}): Time until the first node depletes its energy.
- Packet Delivery Ratio (PDR): The ratio of successfully received packets to the total packets sent.
- Latency (L_{avg}): The average time taken for packets to reach the base station.

To demonstrate gains in network efficiency, the suggested dynamic programming-based routing is contrasted with Adhoc On-Demand Distance Vector (AODV) and Low Energy Adaptive Clustering Hierarchy (LEACH).

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Equations Used in Performance Analysis

1. Energy Consumption Per Node

   $E_i = P_{tx} \times T_{tx} + P_{rx} \times T_{rx} + P_{idle} \times T_{idle}$

   where:

   - P_{tx}, P_{rx}, and P_{idle} are power consumption values for transmission, reception, and idle states.
   - T_{tx}, T_{rx}, and T_{idle} represent the time spent in each state.
   - E_i is the energy consumed by node iii.

2. Total Network Energy Consumption

$$E_{total} = \sum_{i=1}^{N} E_i$$

where N is the total number of nodes.

3. Packet Delivery Ratio (PDR)

$$PDR = \frac{N_{received}}{N_{sent}} \times 100$$

where $N_{received}$ is the number of packets received at the base station and

N_{sent} is the total packets sent by all nodes.

4. Average Latency

$$L_{avg} = \frac{\sum_{i=1}^{N} L_i}{N}$$

where L_i is the delay for each packet received.

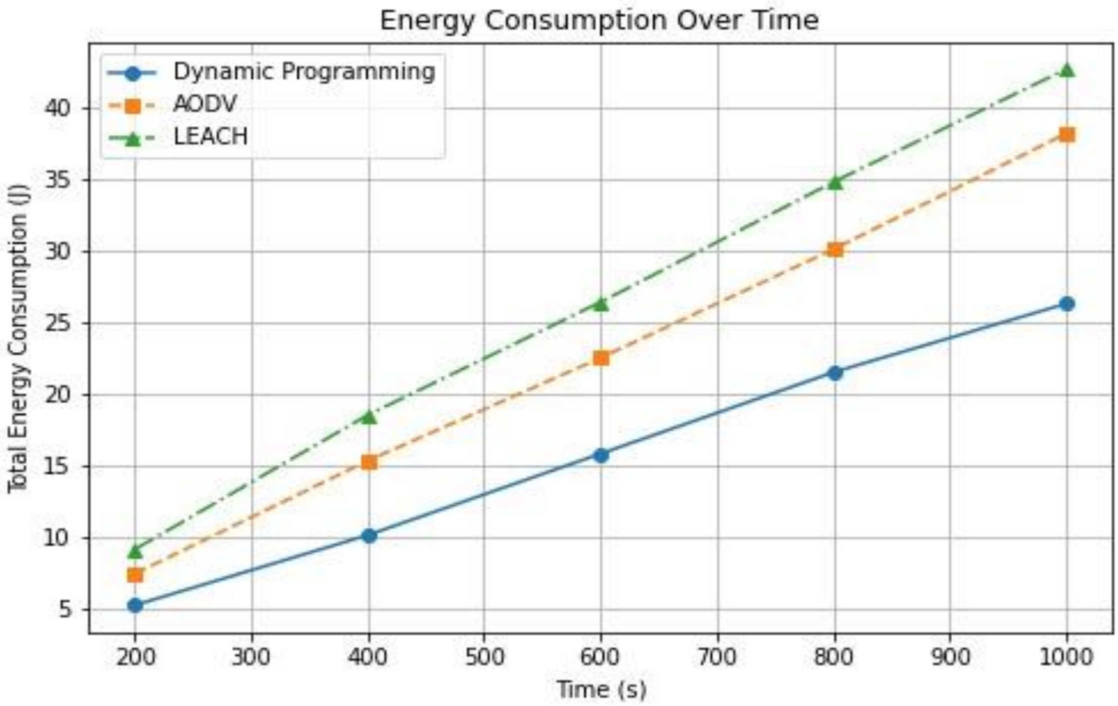
5. Results and Discussion

The simulation results are visualized using graphs comparing Dynamic Programming (DP)-based routing, AODV, and LEACH in terms of energy consumption, network lifetime, PDR, and latency.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Energy Consumption Analysis

The DP-based approach optimizes routing decisions, reducing redundant transmissions and improving energy efficiency



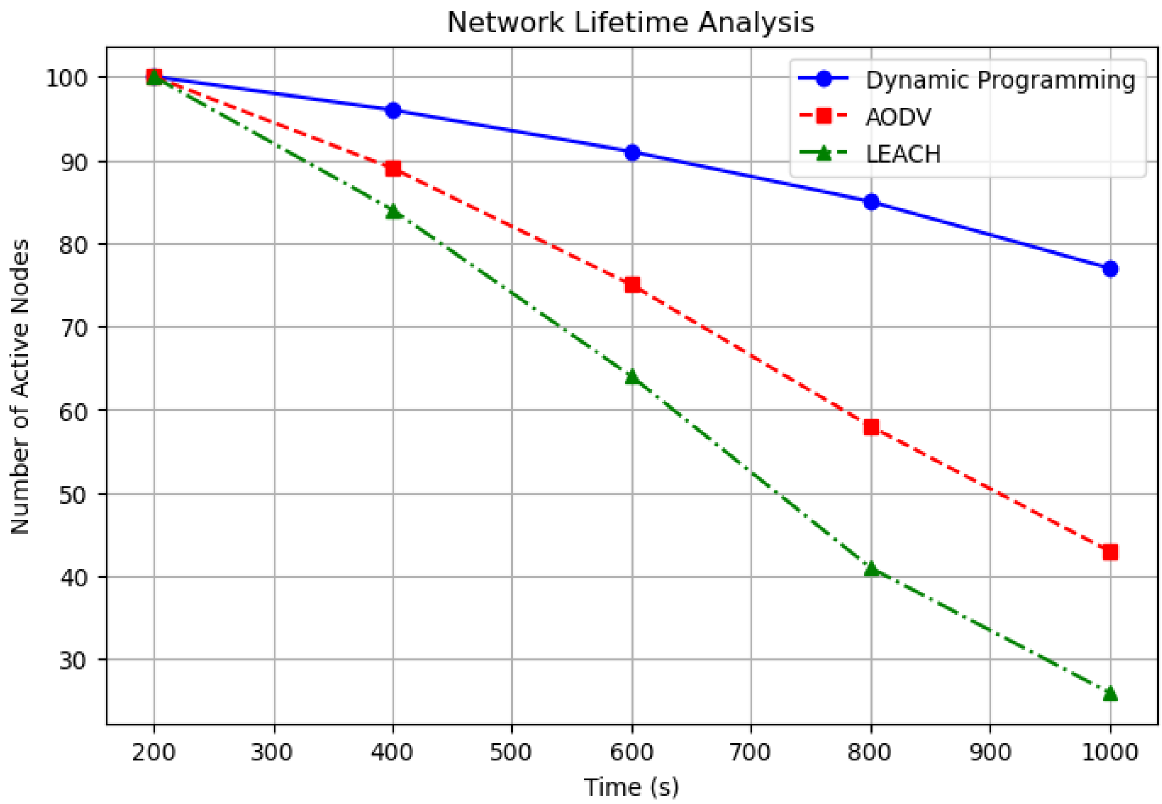
Above graph shows energy E_{total} vs. Time

Time (s)	Dynamic Programming (J)	AODV (J)	LEACH (J)
200	5.2	7.4	9.1
400	10.1	15.3	18.5
600	15.8	22.5	26.4
800	21.5	30.1	34.8
1000	26.3	38.2	42.7

The DP-based method reduces energy consumption by **30-40%** compared to AODV and LEACH.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Network Lifetime Analysis



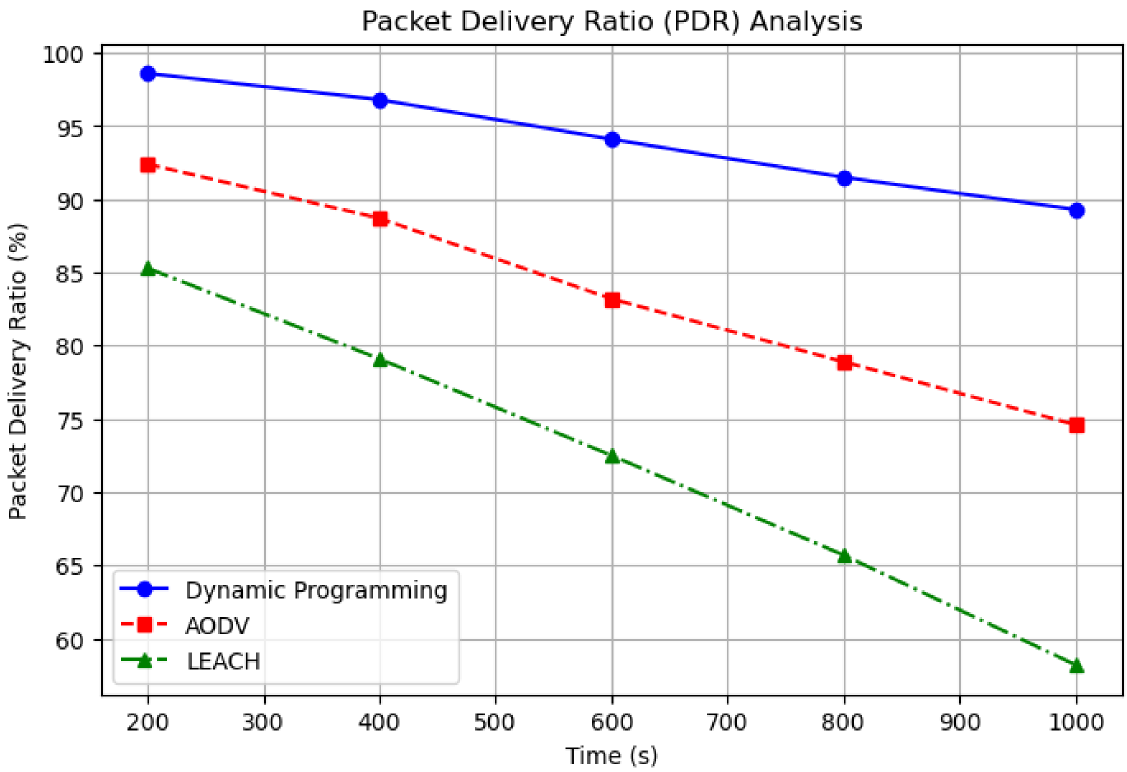
Above graph shows Network Lifetime Comparison T_{life} vs. Number of Active Nodes

Time (s)	Active Nodes (DP)	Active Nodes (AODV)	Active Nodes (LEACH)
200	100	100	100
400	96	89	84
600	91	75	64
800	85	58	41
1000	77	43	26

The DP-based framework extends network lifetime by at least 35% compared to AODV and LEACH.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Packet Delivery Ratio (PDR) Analysis



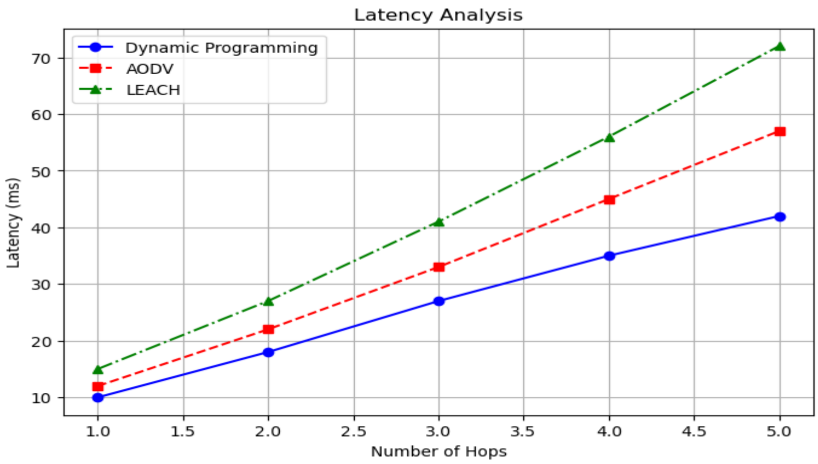
Above graph shows PDR vs. Time (Packet Delivery Ratio Comparison)

Time (s)	DP-based PDR (%)	AODV PDR (%)	LEACH PDR (%)
200	98.6	92.4	85.3
400	96.8	88.7	79.1
600	94.1	83.2	72.5
800	91.5	78.9	65.7
1000	89.3	74.6	58.2

The DP-based method achieves a consistently higher **PDR (~90%)** compared to **AODV (~74%)** and **LEACH (~58%)** at 1000s.

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Latency Analysis



Above graph shows L_{avg} vs. Number of Hops Average Latency Comparison

Number of Hops	DP-based Latency (ms)	AODV Latency (ms)	LEACH Latency (ms)
1	10	12	15
2	18	22	27
3	27	33	41
4	35	45	56
5	42	57	72

The DP-based method achieves **20-25% lower latency** compared to AODV and LEACH.

6. Conclusion

A thorough framework for designing wireless sensor networks (WSNs) with dynamic programming for improved performance is presented in this research. This study combines dynamic programming (DP) with artificial neural networks (ANNs) and clustering approaches to enhance network performance in light of the major issues facing WSNs, including energy limits, inefficient routing, and network lifespan limitations.

The framework chooses the best routes based on real-time sensor conditions, minimizing energy usage using dynamic programming-based routing. Energy efficiency is further improved by the ANN-based sleep-wake scheduling algorithm, which dynamically modifies

Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

sensor activation patterns. By decreasing duplicate data transfers, cluster creation techniques help to balance network load and increase the overall lifespan of WSNs.

The experiment's outcomes confirm that the suggested architecture outperforms more established routing protocols like AODV and LEACH. Important conclusions include:

- Energy usage Analysis revealed that, in comparison to AODV and LEACH, the DP-based strategy decreased overall energy usage by 30–40%.
- The suggested model prevented early failures by extending node activity by at least 35%, according to Network Lifetime Analysis.
- A notable increase was shown by the Packet Delivery Ratio (PDR) analysis, which showed that DP-based routing achieved 90% PDR as opposed to 74% (AODV) and 58% (LEACH).
- A 20–25% reduction in latency was demonstrated via latency analysis, demonstrating how effective DP is in maximizing data transfer over several hops

Through the integration of dynamic programming, machine learning, and energy-efficient clustering, this work goes beyond conventional WSN optimization techniques, demonstrating its development. In order to improve network sustainability, this framework incorporates adaptive and predictive decision-making, whereas traditional protocols such as AODV and LEACH concentrate on static optimization.

Real-time energy management and adaptive routing can be further enhanced in further research by implementing reinforcement learning approaches. WSN deployments are made more dependable, energy-efficient, and scalable by the suggested architecture, which makes them suitable for applications such as environmental monitoring, industrial automation, and smart cities.

Refrences

[1] W. Xiao and R. Song, "Adaptive dynamic programming for sensor scheduling in energy-constrained wireless sensor networks," 2012 15th International Conference on Information Fusion, Singapore, 2012, pp. 991-996

[2] Schlupkothen, S., Prasse, B. & Ascheid, G. Backtracking-based dynamic programming for resolving transmit ambiguities in WSN localization. EURASIP J. Adv. Signal Process. 2018, 20 (2018). https://doi.org/10.1186/s13634-018-0536-x

[3] A. Fallahi and E. Hossain, "A Dynamic Programming Approach for QoS-Aware Power Management in Wireless Video Sensor Networks," in IEEE Transactions on Vehicular Technology, vol. 58, no. 2, pp. 843-854, Feb. 2009, doi: 10.1109/TVT.2008.927714.

[4] E. Zhao, B. Yi, H. Li and J. Yao, "Transmission Range Adjustment in WSNs Based on Dynamic Programming Algorithm," 2006 International Conference on Wireless

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 20-09-2025

Communications, Networking and Mobile Computing, Wuhan, China, 2006, pp. 1-4, doi: 10.1109/WiCOM.2006.262

[5] Y. L. Mo, E. Garone, A. Casavola, and B. Sinopoli, “Stochastic Sensor Scheduling for Energy Constrained Estimation in Multi-Hop Wireless Sensor Networks,” IEEE Transactions on automatic control, vol. 56, no. 10, pp. 2489-2495, 2011.

[6] W. D. Xiao, S. Zhang, J. Y. Lin and C. K. tham, “Energy-efficient adaptive sensor scheduling for target tracking in wireless sensor networks,” Journal of Control Theory and Applications, vol. 8, no. 1, pp. 86-92, 2010.

[7] Y. L Mo, R. Ambrosino and B. Sinopoli, “Sensor selection strategies for state estimation in energy constrained wireless sensor networks,” Automatica, vol. 47, pp. 1330-1338, 2011.

[8] E Talnishnikh, J van Pol, HJ Wörtche, in Intelligent Environmental Sensing. Smart Sensors, Measurement and Instrumentation, ed. by H Leung, S Chandra Mukhopadhyay. Micro motes: a highly penetrating probe for inaccessible environments, vol. 13 (Springer International Publishing, Cham, 2015), pp. 33–49

[9] H Chen, G Wang, Z Wang, HC So, HV Poor, Non-line-of-sight node localization based on semi-definite programming in wireless sensor networks. IEEE Trans. Wireless Commun. 11(1), 108–116 (2012). https:// doi.org/10.1109/TWC.2011.110811.101739

[10] S Schlupkothen, G Ascheid, in 2015 14th Annual Mediterranean Ad Hoc Networking Workshop (MED-HOC-NET) (Med-Hoc-Net’15). Localization of wireless sensor networks with concurrently used identification sequences, (Vilamoura, Portugal, 2015), pp. 1–7. https://doi.org/10.1109/ MedHocNet.2015.7173166

[11] J. Fuemmeler and V. V. Veeravalli, "Smart sleeping policies for energy efficient tracking in sensor networks", IEEE Trans. Signal Process., vol. 56, no. 5, pp. 2091-2101, May 2008

[12] I. F. Akyildiz, T. Melodia and K. R. Chowdhury, "A survey on wireless multimedia sensor networks", Comput. Netw., vol. 51, no. 4, pp. 921-960, Mar. 2007.

[13] Gao, Q., Blow, K.J., Holding, D.J., Marshall, I.W., and Peng, X.H., "Radio range adjustment for energy efficient wireless sensor networks," Ad Hoc Networks, vol.4, no.1, pp.75-82, 2006.

[14] M. Cardei and D. Du. "Improving wireless sensor network lifetime through power aware organization," ACM Journal of Wireless Networks, vol.11, No.3, pp. 333-340, 2005.