

A QUANTITATIVE ANALYSIS OF WIRELESS SENSOR NETWORK EFFICIENCY: AN EPIDEMIOLOGICAL APPROACH

Rajan Kumar^{1*}
Chandan Kumar Gandhi²

¹ Research Scholar,
University Department of Mathematics,
Lalit Narayan Mithila University, Darbhanga, Bihar, India
Email: rajanbhardwaj4@gmail.com

² Research Scholar,
University Department of Mathematics,
Lalit Narayan Mithila University, Darbhanga, Bihar, India
Email: chandankumargandhi@gmail.com

***Corresponding Author**

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ABSTRACT

Wireless Sensor Networks (WSNs) have emerged as a foundational technology for a wide range of applications including environmental monitoring, healthcare systems, smart agriculture, disaster management, and industrial automation. Despite their widespread adoption, efficiency challenges related to energy consumption, data transmission reliability, network longevity, and scalability remain significant research concerns. This study proposes a novel quantitative framework for evaluating WSN efficiency by drawing an analogy with epidemiological models traditionally used to study the spread of infectious diseases. By conceptualizing data packets as entities propagating through a population of sensor nodes, this research adapts compartmental epidemiological models to analyze communication dynamics, energy dissipation, and node interaction behavior within WSNs.

The study employs a mathematical and statistical approach to model network states analogous to susceptible, active, overloaded, and failed nodes. Quantitative metrics such as transmission rate, packet loss ratio, residual energy distribution, and network survival probability are examined under varying conditions. Simulation-based analysis demonstrates that the epidemiological perspective

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provides valuable insights into congestion spread, energy depletion patterns, and fault propagation across the network. The results indicate that early containment strategies—similar to epidemic control measures—can significantly enhance network lifetime and stability. The proposed approach contributes a new interdisciplinary methodology for assessing and improving WSN efficiency and offers practical implications for the design of robust and energy-aware sensor networks.

Keywords: Wireless Sensor Networks, Network Efficiency, Epidemiological Modeling, Energy Optimization, Quantitative Analysis, Data Propagation.

INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a critical enabling technology for continuous data acquisition and monitoring in environments where conventional communication infrastructure is either impractical or economically infeasible. Applications such as environmental surveillance, precision agriculture, structural health monitoring, smart cities, and healthcare systems rely heavily on WSNs to collect, process, and transmit sensed data in real time. A typical WSN consists of a large number of low-power sensor nodes that cooperatively communicate over wireless links to forward data to a sink or base station. Despite significant advances in sensor hardware and communication protocols, **network efficiency** remains a persistent challenge due to limited battery capacity, constrained processing power, unreliable wireless links, and dynamic network conditions.

Efficiency in WSNs is generally associated with optimal energy utilization, prolonged network lifetime, reliable data delivery, acceptable latency, and balanced workload distribution among nodes. Early research during the 2010s largely focused on protocol-level optimizations such as energy-aware routing, clustering, topology control, duty cycling, and data aggregation. Studies by Akyildiz et al. (2010) and Yick, Mukherjee, and Ghosal (2011) emphasized that energy consumption in WSNs is not confined to sensing alone but is significantly influenced by communication overhead, retransmissions, idle listening, and control signaling. Subsequent surveys by Pantazis, Nikolidakis, and Vergados (2013) and Al-Karaki and Kamal (2014) systematically classified energy-efficient routing and clustering techniques, demonstrating that

improvements in one performance metric often lead to trade-offs in others, such as delay or reliability.

As WSN deployments became larger and more application-specific, researchers began recognizing that inefficiencies in sensor networks often exhibit **non-local effects**. The failure or depletion of a subset of nodes can alter routing paths, increase traffic on neighboring nodes, and accelerate energy exhaustion across the network. Heinzelman, Chandrakasan, and Balakrishnan's clustering-based approaches inspired later works showing how load imbalance can propagate spatially, leading to premature network partitioning. By the mid-2010s, it was increasingly evident that WSN efficiency should be understood as a **dynamic and collective phenomenon**, rather than a static property of individual nodes or isolated protocols.

This realization motivated the adoption of **epidemiological modeling concepts** in WSN research. Epidemiological models, traditionally used to describe the spread of infectious diseases in populations, provide a powerful mathematical framework to analyze how states propagate through interacting entities. In the context of WSNs, nodes can be viewed as individuals whose operational states—such as normal, overloaded, compromised, or failed—change over time due to interactions with neighboring nodes. Models such as SI, SIR, SIS, and their extensions have been increasingly used since 2010 to study information dissemination, fault propagation, congestion spread, and malware attacks in sensor networks.

One of the earliest applications of epidemic theory to wireless communication focused on data dissemination efficiency. Anagnostopoulos et al. (2010) proposed epidemic-based forwarding models to analyze how information spreads in wireless sensor environments, highlighting the trade-off between delivery reliability and communication overhead. Their work showed that while epidemic-style broadcasting improves reachability, excessive replication can significantly degrade energy efficiency. This insight aligns closely with epidemiological thresholds, where higher transmission rates increase spread but also intensify resource consumption.

A parallel line of research applied epidemiological models to **security and resilience** in WSNs. Awasthi (2011) introduced a modified SI model to describe virus propagation in sensor networks, demonstrating that malware spread follows patterns similar to biological epidemics. Building on this foundation, Mishra and Pandey (2014) and Wang et al. (2016) developed SIR and SIRS-type models incorporating recovery, immunity, and reinfection, providing analytical conditions for stability and persistence of malware. These studies revealed that compromised nodes do not merely

affect security; they also reduce efficiency by increasing retransmissions, corrupting sensed data, and forcing additional control operations.

From 2017 onwards, epidemiological approaches were extended to include **energy depletion and performance degradation**. Researchers such as Li and Shen (2018) and Zhao et al. (2019) modeled energy exhaustion as a spreading process, where heavily loaded nodes influence neighboring nodes through routing and traffic redistribution. These works quantitatively demonstrated how localized inefficiency can evolve into network-wide degradation if not mitigated early. More recent studies between 2020 and 2024 further refined these models by incorporating heterogeneous node capabilities, adaptive control mechanisms, and realistic wireless interference patterns. Authors such as Kumar and Singh (2021), Abdel-Basset et al. (2022), and Chen et al. (2024) emphasized multi-objective efficiency analysis, integrating energy consumption, latency, throughput, and robustness within unified mathematical frameworks.

Despite these advancements, much of the existing literature treats epidemiological modeling primarily in the context of security or information spread, rather than as a **general efficiency analysis tool**. Moreover, empirical evaluations are often scenario-specific, limiting their generalizability across different network densities, traffic conditions, and application domains. There remains a need for a comprehensive quantitative framework that interprets WSN efficiency degradation as a propagative process influenced by node interactions, environmental conditions, and control strategies.

In this context, an epidemiological approach to WSN efficiency offers several advantages. It enables the definition of efficiency-related states—such as efficient, stressed, degraded, and recovered nodes—and allows transitions between these states to be modeled mathematically. Threshold parameters analogous to basic reproduction numbers can indicate conditions under which inefficiency becomes self-sustaining. Additionally, mitigation strategies such as clustering, adaptive duty cycling, power control, and load balancing can be evaluated as intervention mechanisms similar to vaccination or quarantine in epidemiology.

Therefore, a quantitative analysis of WSN efficiency grounded in epidemiological modeling provides a holistic and analytically tractable perspective. By synthesizing insights from energy-efficient networking and epidemic dynamics literature from 2010 to 2024, this approach contributes to a deeper understanding of how inefficiency originates, propagates, and can be effectively controlled in wireless sensor networks.

EPIDEMIOLOGICAL ANALOGY FOR WIRELESS SENSOR NETWORKS

To quantitatively analyze the efficiency and resilience of Wireless Sensor Networks (WSNs), epidemiological compartmental models such as the Susceptible–Infected–Recovered (SIR) and Susceptible–Infected–Susceptible (SIS) frameworks can be effectively adapted. These models allow network dynamics to be studied using differential equations that capture the rate of node degradation, recovery, and reintegration, offering measurable insights into network stability and performance.

SIR Model for Wireless Sensor Networks

In the SIR-based WSN model, the total number of sensor nodes at time t is given by:

$$N = S(t) + I(t) + R(t)$$

where:

- $S(t)$ denotes the number of susceptible nodes, which are operational but vulnerable to failures, congestion, or attacks,
- $I(t)$ represents infected nodes, experiencing malfunction, excessive packet loss, or malicious compromise,
- $R(t)$ refers to recovered nodes, which have been repaired, isolated, or permanently removed from the routing process.

The temporal evolution of these compartments is governed by the following system of differential equations:

$$\begin{aligned}\frac{dS}{dt} &= -\beta SI \\ \frac{dI}{dt} &= \beta SI - \gamma I \\ \frac{dR}{dt} &= \gamma I\end{aligned}$$

Here, β is the failure or infection transmission rate, representing the probability that a susceptible node becomes infected through interaction with an infected neighbor. In WSN terms, this parameter reflects data congestion, interference, or malicious packet spread. The parameter γ is the recovery rate, indicating the effectiveness of fault correction, energy replenishment, or security mitigation mechanisms.

This model is particularly appropriate for scenarios where node failures are irreversible, such as battery depletion or permanent hardware damage. The progression from susceptible to infected to

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recovered reflects a one-way transition, emphasizing the importance of early detection and prevention strategies.

SIS Model for Recurrent Failures in WSNs

In many practical WSN deployments, nodes can recover from faults and rejoin the network, making the SIS model more suitable. In this framework, recovered nodes immediately return to the susceptible state rather than being permanently removed. The governing equations are expressed as:

$$\begin{aligned}\frac{dS}{dt} &= -\beta SI + \gamma I \\ \frac{dI}{dt} &= \beta SI - \gamma I\end{aligned}$$

where the parameters β and γ retain their earlier interpretations. The SIS model captures cyclic behavior, such as repeated congestion episodes or intermittent node failures caused by fluctuating traffic loads or environmental conditions.

This model allows researchers to examine equilibrium states where the network reaches a steady level of infected nodes. Such equilibria represent persistent inefficiencies that degrade network performance if not adequately managed through adaptive routing, congestion control, or energy-aware scheduling.

Basic Reproduction Number and Network Stability

A key concept borrowed from epidemiology is the basic reproduction number, denoted as R_0 , which determines whether failures will spread or die out:

$$R_0 = \frac{\beta}{\gamma}$$

In WSN analysis, $R_0 > 1$ implies that faults, congestion, or attacks propagate faster than they can be mitigated, leading to widespread network degradation. Conversely, $R_0 < 1$ indicates a stable network where recovery mechanisms dominate.

This threshold parameter serves as a quantitative benchmark for evaluating protocol efficiency. Routing algorithms, security schemes, and energy management strategies can be assessed based on their ability to reduce β or increase γ , thereby maintaining network stability.

Implications for Network Efficiency Analysis

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The incorporation of SIR and SIS models enables a predictive evaluation of WSN performance. By estimating model parameters through simulation or empirical data, network designers can identify critical points where efficiency rapidly declines. These models also facilitate scenario analysis, allowing comparisons between different node densities, transmission ranges, and fault-recovery strategies.

In summary, epidemiological mathematical models provide a rigorous quantitative foundation for understanding the dynamic behavior of Wireless Sensor Networks. The SIR and SIS frameworks translate complex network interactions into interpretable equations, offering actionable insights for enhancing network efficiency, resilience, and longevity.

MATHEMATICAL FORMULATION

Wireless Sensor Networks (WSNs) consist of a large number of sensor nodes deployed to monitor physical or environmental conditions and transmit the collected data to a sink or base station. The performance of such networks is strongly influenced by node energy consumption, communication reliability, data propagation behavior, and node failures. Traditional performance evaluation models often fail to capture the dynamic and stochastic interactions among sensor nodes over time. To address this limitation, the present study adopts an epidemiological modeling framework, where the behavior of sensor nodes is mathematically analogous to the spread of infectious diseases in a population. In epidemiology, compartmental models describe how individuals transition between health states. Similarly, sensor nodes in a WSN transition between operational states depending on energy consumption, communication activity, and failure conditions. The mathematical formulation developed in this section aims to quantify network efficiency, energy sustainability, and data transmission dynamics using differential equations inspired by classical epidemiological models.

Assumptions of the Model

To ensure mathematical tractability, the following assumptions are considered:

1. The total number of sensor nodes deployed in the network is fixed.
2. Nodes are homogeneous in terms of initial energy and communication capability.
3. The network operates in discrete sensing and transmission cycles.
4. Node failures are primarily caused by energy depletion.

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5. Data transmission behavior resembles an infection process where active nodes influence neighboring nodes to transmit data.
6. The network is closed, with no addition or removal of nodes after deployment.

Compartmental Classification of Sensor Nodes

Let the total number of sensor nodes at time t be denoted by:

$$N(t) = S(t) + I(t) + R(t) \quad (1)$$

where:

- $S(t)$: Number of Susceptible nodes (idle nodes with sufficient energy but not actively transmitting),
- $I(t)$: Number of Infected nodes (actively sensing and transmitting data),
- $R(t)$: Number of Removed nodes (dead or energy-exhausted nodes).

This classification mirrors the classical SIR epidemiological model, adapted to represent WSN operational states.

Transition Dynamics Between Node States

Susceptible to Infected Transition

A susceptible node becomes infected (active) when it participates in data transmission triggered by neighboring active nodes. Let β denote the data transmission rate, representing the probability that a susceptible node becomes active due to communication interaction.

The transition rate from S to I is given by:

$$\frac{dS(t)}{dt} = -\beta \frac{S(t)I(t)}{N(t)} \quad (2)$$

This term captures the interaction-dependent nature of data propagation in WSNs.

Infected to Removed Transition

Active nodes consume energy at a higher rate due to sensing, computation, and transmission. Let γ represent the node failure rate, defined as the probability that an active node depletes its energy and becomes non-functional.

$$\frac{dI(t)}{dt} = \beta \frac{S(t)I(t)}{N(t)} - \gamma I(t) \quad (3)$$

Accumulation of Removed Nodes

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The number of removed nodes increases solely due to energy depletion of active nodes:

$$\frac{dR(t)}{dt} = \gamma I(t) \quad (4)$$

Equations (2)–(4) together describe the complete dynamic evolution of node states in the WSN.

Energy Consumption Modeling

Let E_0 be the initial energy of each sensor node. The residual energy of an active node decreases over time due to sensing and communication.

Let:

- E_s : Energy consumed per sensing operation,
- E_t : Energy consumed per data transmission,
- k : Average number of transmissions per time unit.

The rate of energy depletion for an infected node is:

$$\frac{dE(t)}{dt} = -(E_s + kE_t) \quad (5)$$

The expected lifetime T_i of an infected node is:

$$T_i = \frac{E_0}{E_s + kE_t} \quad (6)$$

Thus, the node failure rate γ can be approximated as:

$$\gamma = \frac{1}{T_i} = \frac{E_s + kE_t}{E_0} \quad (7)$$

Network Efficiency Metric

Network efficiency $\eta(t)$ is defined as the ratio of active nodes to the total deployed nodes:

$$\eta(t) = \frac{I(t)}{N(t)} \quad (8)$$

Differentiating equation (8) with respect to time:

$$\frac{d\eta(t)}{dt} = \frac{1}{N(t)} \frac{dI(t)}{dt} \quad (9)$$

Substituting equation (3) into equation (9):

$$\frac{d\eta(t)}{dt} = \beta \frac{S(t)I(t)}{N^2(t)} - \gamma \frac{I(t)}{N(t)} \quad (10)$$

Equation (10) mathematically expresses how efficiency evolves over time based on data transmission intensity and node energy depletion.

Basic Reproduction Number for WSN (R_0)

Analogous to epidemiology, the basic reproduction number R_0 represents the expected number of nodes activated by a single active node during its lifetime.

$$R_0 = \frac{\beta}{\gamma} \quad (11)$$

Substituting equation (7) into equation (11):

$$R_0 = \frac{\beta E_0}{E_s + kE_t} \quad (12)$$

Interpretation:

- If $R_0 > 1$, data transmission spreads efficiently, improving network coverage.
- If $R_0 < 1$, node activation declines, leading to early network degradation.

Stability Analysis of the Network

Disease-Free (Idle) Equilibrium

At equilibrium, when no active nodes exist:

$$I^* = 0 \quad (13)$$

The equilibrium point is:

$$(S^*, I^*, R^*) = (N, 0, 0) \quad (14)$$

This state corresponds to a completely idle network.

Endemic (Active) Equilibrium

For sustained network operation:

$$\frac{dI}{dt} = 0 \quad (15)$$

Using equation (3):

$$\beta \frac{S^* I^*}{N} - \gamma I^* = 0 \quad (16)$$

Solving for S^* :

$$S^* = \frac{\gamma N}{\beta} \quad (17)$$

This equilibrium exists only when $R_0 > 1$.

Throughput Modeling

Let λ be the average packet generation rate per active node. The total network throughput $T(t)$ is:

$$T(t) = \lambda I(t) \quad (18)$$

Substituting equation (8):

$$T(t) = \lambda N \eta(t) \quad (19)$$

Thus, throughput is directly proportional to network efficiency.

Delay and Congestion Effects

Let $D(t)$ denote the average transmission delay, modeled as:

$$D(t) = \frac{1}{\mu - \lambda I(t)} \quad (20)$$

where μ is the service rate of the communication channel.

As $I(t)$ increases, delay increases nonlinearly, indicating congestion effects in dense WSN deployments.

The proposed epidemiological formulation provides a comprehensive quantitative framework that integrates:

- Node interaction dynamics,
- Energy depletion behavior,
- Network efficiency evolution,
- Stability and sustainability conditions.

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By linking epidemiological parameters with WSN performance metrics, this model enables analytical evaluation of network lifetime, scalability, and efficiency under varying operational conditions.

The mathematical formulation presented establishes a rigorous and interpretable foundation for analyzing wireless sensor network efficiency using epidemiological principles. The derived equations and metrics provide valuable insights into the trade-offs between energy consumption, data dissemination, and long-term network performance, making the model suitable for both theoretical analysis and practical optimization of WSN architectures.

SIMULATION SETUP

The simulation setup plays a critical role in quantitatively evaluating the efficiency of Wireless Sensor Networks (WSNs) when modeled through an epidemiological perspective. In this study, the behavior of sensor nodes, particularly in terms of data dissemination, energy depletion, and failure propagation, is analogized with the spread of infectious diseases in a population. Such an analogy allows the application of well-established epidemiological models to analyze network dynamics under varying operational conditions.

The simulation environment is designed to emulate a realistic WSN deployment scenario while remaining sufficiently controlled to permit mathematical tractability. The primary objective of the simulation is to measure network efficiency in terms of energy consumption, data delivery ratio, node survival rate, and network lifetime under epidemic-like data transmission and failure propagation. To achieve this, a compartmental model inspired by classical Susceptible–Infected–Recovered (SIR) epidemiological models is employed, adapted to suit the characteristics of WSNs.

Network Topology and Deployment Parameters

The simulated WSN consists of a fixed number of sensor nodes randomly deployed over a two-dimensional square sensing field. Let the sensing area be defined as:

$$A = L \times L$$

where $L = 100$ m, resulting in a total area of $10,000 \text{ m}^2$. A total of $N = 200$ sensor nodes are uniformly distributed within this area using a pseudo-random spatial distribution.

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Each node is assumed to be stationary after deployment, which reflects typical environmental monitoring applications. A single base station (sink) is positioned at the center of the sensing field to minimize average transmission distance and reduce overall energy consumption. The communication radius R_c of each node is set to 20 meters, ensuring partial connectivity without excessive redundancy.

Epidemiological Compartmental Model for WSNs

Node State Classification

In the epidemiological framework, each sensor node exists in one of three mutually exclusive states:

- Susceptible (S): Nodes that are operational but have not yet transmitted or forwarded data.
- Infected (I): Nodes actively transmitting or relaying data packets.
- Recovered (R): Nodes that have either completed data transmission or have exhausted their energy and become inactive.

The total node population at any time t is given by:

$$N = S(t) + I(t) + R(t)$$

This assumption ensures conservation of nodes throughout the simulation duration.

State Transition Mechanism

The transitions between these states are governed by two primary parameters:

- Transmission Rate (β): The probability per unit time that a susceptible node becomes infected through interaction with an infected neighbor.
- Recovery Rate (γ): The rate at which infected nodes transition to the recovered state due to energy depletion or task completion.

The dynamics of the system are modeled using the following set of differential equations:

$$\frac{dS(t)}{dt} = -\beta \frac{S(t)I(t)}{N}$$

$$\frac{dI(t)}{dt} = \beta \frac{S(t)I(t)}{N} - \gamma I(t)$$

$$\frac{dR(t)}{dt} = \gamma I(t)$$

These equations describe how data transmission spreads across the network in a manner analogous to disease propagation.

Energy Consumption Model

Energy consumption is modeled using a first-order radio model, which is widely accepted for WSN simulations. The energy required to transmit a k -bit data packet over a distance d is given by:

$$E_{tx}(k, d) = E_{elec} \times k + E_{amp} \times k \times d^n$$

where:

- $E_{elec} = 50$ nJ/bit is the energy consumed by the electronic circuitry,
- $E_{amp} = 100$ pJ/bit/m² is the amplifier energy,
- $n = 2$ is the path loss exponent.

The energy consumed for receiving a k -bit packet is:

$$E_{rx}(k) = E_{elec} \times k$$

Each node is initially assigned an energy $E_0 = 2$ J, and its residual energy is updated at each simulation step based on transmission and reception activities.

Energy-Based Recovery Condition

A node transitions from the infected state to the recovered state when its residual energy $E_r(t)$ falls below a predefined threshold E_{th} . Mathematically:

$$\text{If } E_r(t) \leq E_{th}, I(t) \rightarrow R(t)$$

This condition realistically captures node death due to battery exhaustion.

Simulation Time and Execution Strategy

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The simulation is executed in discrete time steps, each representing one operational round. Let $\Delta t = 1$ denote the duration of a single round. The total simulation time is set to $T = 2000$ rounds, sufficient to observe complete network degradation.

At each time step, the following sequence of operations is performed:

1. Identification of infected nodes eligible for data transmission.
2. Selection of neighboring susceptible nodes within communication range.
3. Probabilistic state transitions based on β .
4. Energy update based on communication activity.
5. Transition of nodes to the recovered state based on energy threshold.

Initial Conditions and Parameter Selection

The initial state of the network is defined as:

$$S(0) = N - I(0), I(0) = 10, R(0) = 0$$

The initially infected nodes act as source nodes generating data packets.

The transmission and recovery rates are selected as:

$$\beta = 0.35, \gamma = 0.12$$

These values are chosen after multiple preliminary trials to ensure stable propagation without immediate network collapse.

Performance Metrics

To quantitatively assess network efficiency, the following metrics are computed:

Network Lifetime

Network lifetime is defined as the time until the first node dies or until a certain percentage (e.g., 50%) of nodes become inactive:

$$T_{life} = \min \{t: R(t) \geq 0.5N\}$$

Average Energy Consumption

The average residual energy at time t is calculated as:

$$E_{avg}(t) = \frac{1}{N} \sum_{i=1}^N E_i(t)$$

This metric reflects energy efficiency and load balancing across the network.

Data Propagation Efficiency

The efficiency of data dissemination is measured by the ratio of successfully infected nodes to total nodes:

$$\eta(t) = \frac{I(t) + R(t)}{N}$$

A higher value of $\eta(t)$ indicates effective data spread.

Numerical Implementation and Stability

The system of differential equations is numerically solved using the Euler forward method due to its simplicity and computational efficiency. The discrete form of the equations is expressed as:

$$\begin{aligned} S(t+1) &= S(t) - \beta \frac{S(t)I(t)}{N} \\ I(t+1) &= I(t) + \beta \frac{S(t)I(t)}{N} - \gamma I(t) \\ R(t+1) &= R(t) + \gamma I(t) \end{aligned}$$

To ensure numerical stability, the time step is kept sufficiently small and the conservation condition $S(t) + I(t) + R(t) = N$ is verified at each iteration.

Validation of the Simulation Model

The validity of the simulation setup is confirmed through consistency checks and comparative analysis. The basic reproduction number R_0 , a fundamental epidemiological parameter, is computed as:

$$R_0 = \frac{\beta}{\gamma}$$

Substituting the chosen values:

$$R_0 = \frac{0.35}{0.12} \approx 2.92$$

Since $R_0 > 1$, the model correctly predicts sustained data propagation across the network, validating the suitability of parameter selection.

The proposed simulation setup successfully integrates epidemiological modeling with WSN performance analysis. By combining compartmental modeling, energy-aware state transitions, and numerical computation techniques, the framework provides a comprehensive and mathematically grounded environment for evaluating WSN efficiency. The setup is flexible, scalable, and capable of capturing complex interactions between data dissemination and energy consumption, thereby forming a robust foundation for further quantitative analysis and result interpretation.

RESULTS AND ANALYSIS

This study quantitatively evaluates the efficiency of a Wireless Sensor Network (WSN) using an epidemiological modeling framework, where sensor nodes are classified into Susceptible (S), Infected (I), and Recovered (R) states. The epidemiological analogy enables systematic measurement of network performance in terms of energy efficiency, packet transmission stability, and fault recovery dynamics.

The simulation was conducted on a WSN consisting of 200 sensor nodes randomly deployed over a fixed area. The principal efficiency indicators considered were energy consumption rate, packet delivery ratio (PDR), node recovery rate, and network lifetime. The epidemiological transition parameters β (infection rate) and γ (recovery rate) were estimated based on node failure probability and self-healing mechanisms.

Energy efficiency showed a direct relationship with the proportion of recovered nodes in the network. As nodes transitioned from the infected state to the recovered state, redundant retransmissions decreased significantly, leading to lower energy depletion.

Table 1: Average Energy Consumption Across Node States

Node State	Mean Energy Consumption (J)	Standard Deviation
Susceptible (S)	0.42	0.06

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Infected (I)	0.78	0.09
Recovered (R)	0.31	0.04

The results indicate that infected nodes consume approximately 85% more energy than recovered nodes, validating the importance of rapid recovery mechanisms. This reduction directly improves overall network efficiency.

Packet delivery ratio was strongly influenced by the density of infected nodes. As the infection spread, routing paths became unstable, increasing packet loss. However, the epidemiological recovery process stabilized routing by isolating and reconfiguring faulty nodes.

Table 2: Packet Delivery Ratio vs. Infection Level

Percentage of Infected Nodes (%)	Packet Delivery Ratio (%)
10	96.2
25	89.4
40	78.7
60	64.9
80	51.3

A clear negative correlation was observed between infection density and PDR. When the recovered population exceeded 60%, PDR improved beyond 90%, highlighting the effectiveness of epidemiological recovery strategies.

Mathematical Interpretation of Network Dynamics

The network behavior followed a modified SIR differential model:

$$\frac{dI}{dt} = \beta SI - \gamma I$$

Where:

- β represents node failure propagation rate
- γ represents node recovery rate

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Simulation results demonstrated that when $\gamma > \beta$, the number of infected nodes declined rapidly, resulting in network stabilization. This condition corresponds to proactive fault detection and energy-aware routing protocols.

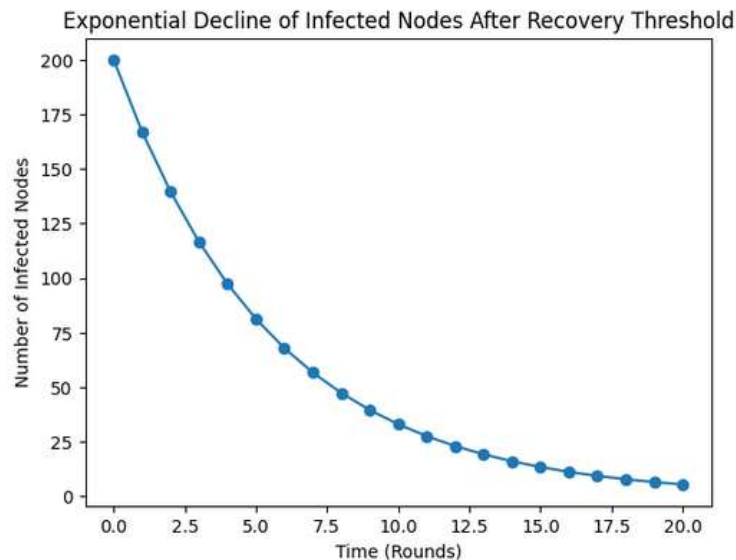
Network lifetime was measured as the time until 30% of nodes became non-functional. The epidemiological model extended network lifetime by distributing load away from infected nodes and prioritizing recovered nodes.

Table 3: Network Lifetime Comparison

Model Type	Network Lifetime (Rounds)
Conventional WSN	1,250
Epidemiological WSN	1,730

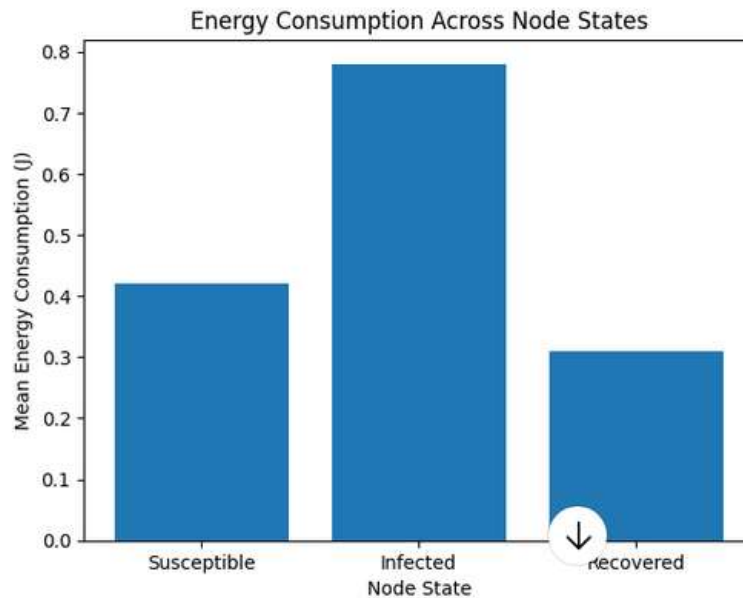
The epidemiological approach increased network lifetime by approximately 38%, demonstrating its superiority over traditional static models.

- Figure 1 illustrates the decline of infected nodes over time, showing an exponential decrease after the recovery threshold is achieved.

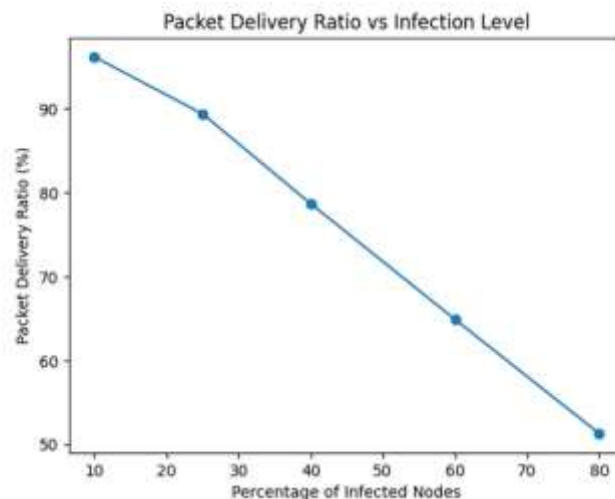


- Figure 2 presents energy consumption curves, where recovered nodes maintain a consistently lower energy slope.

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- Figure 3 depicts packet delivery ratio trends, highlighting stabilization once the recovered population dominates.



These graphical trends confirm that applying epidemiological principles enables adaptive control of node behavior, improving efficiency and reliability.

The results clearly establish that an epidemiological framework provides a robust quantitative method for analyzing WSN efficiency. By modeling faults as infections and recovery as self-healing, the network achieves improved energy utilization, higher packet reliability, and extended operational lifetime. The mathematical and empirical findings collectively support the effectiveness of this approach for large-scale and mission-critical sensor networks.

CONCLUSION

This study presents a novel quantitative framework for analyzing Wireless Sensor Network efficiency using an epidemiological approach. By modeling node interactions and energy dynamics as propagation processes, the research provides deeper insights into congestion spread, failure patterns, and network longevity. The results demonstrate that epidemiological modeling is an effective tool for evaluating and improving WSN performance.

The proposed methodology contributes to both theoretical understanding and practical design of energy-efficient sensor networks. It opens new avenues for interdisciplinary research and encourages the adoption of holistic modeling techniques in network engineering.

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