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ASSESSING WIRELESS SENSOR NETWORK PERFORMANCE USING EPIDEMIOLOGICAL MODELING: A QUANTITATIVE STUDY

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ABSTRACT

Wireless Sensor Networks (WSNs) are widely used in applications such as environmental monitoring, healthcare, industrial automation, and smart cities. Despite their importance, WSNs face persistent challenges related to energy efficiency, data reliability, fault propagation, and network longevity. Traditional performance evaluation methods often rely on protocol-level simulations or mathematical optimization techniques that may fail to capture the dynamic and collective behavior of sensor nodes under varying conditions. In recent years, epidemiological modeling—originally developed to study the spread of infectious diseases—has emerged as a promising interdisciplinary approach for analyzing complex networked systems.

This study explores the application of epidemiological models to assess the performance of Wireless Sensor Networks. By drawing analogies between disease transmission and data or fault propagation among sensor nodes, the research adopts compartmental models such as Susceptible–Infected–Recovered (SIR) and Susceptible–Exposed–Infected–Recovered (SEIR) to quantitatively analyze network behavior. The proposed framework maps sensor states to epidemiological compartments and evaluates key performance metrics, including packet delivery ratio, energy consumption, network stability, and resilience against node failures.

Through analytical modeling and numerical simulations, the study demonstrates that epidemiological models can effectively capture temporal dynamics, congestion effects, and recovery mechanisms in WSNs. The results indicate that infection and recovery rates strongly influence network throughput and lifetime, providing valuable insights for protocol design and network management. The paper concludes that epidemiological modeling offers a flexible and scalable tool for WSN performance evaluation and can complement conventional analytical and simulation-based methods.

Keywords: Wireless Sensor Networks, Epidemiological Modeling, SIR Model, Network Performance, Quantitative Analysis.

INTRODUCTION

Wireless Sensor Networks (WSNs) have become a foundational technology for modern monitoring and data acquisition systems. They are widely used in environmental monitoring,

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healthcare, industrial automation, smart agriculture, military surveillance, and disaster management. A typical WSN consists of a large number of low-power sensor nodes that cooperatively sense, process, and transmit data to a sink or base station. Despite their broad applicability, WSNs face persistent performance challenges related to energy efficiency, network reliability, congestion, packet loss, latency, and node failures. As network scale and application complexity increase, traditional analytical and simulation-based performance evaluation methods often fail to capture the dynamic and stochastic behavior of WSNs under real-world conditions.

Over the last decade, researchers have increasingly recognized similarities between information propagation in networks and the spread of infectious diseases in populations. This observation has led to the adoption of epidemiological modeling as a novel and powerful analytical framework for studying communication networks. Epidemiological models, originally developed to understand disease transmission dynamics, provide mathematical tools to describe how states spread over time through interacting entities. When applied to WSNs, these models can represent packet dissemination, congestion propagation, node failures, and malicious attacks as epidemic processes. This interdisciplinary approach offers a quantitative and system-level understanding of network behavior that is difficult to achieve using conventional methods.

Early research between 2010 and 2013 primarily focused on applying basic Susceptible–Infected–Recovered (SIR) and Susceptible–Infected–Susceptible (SIS) models to wireless and ad hoc networks. Pastor-Satorras and Vespignani (2011) demonstrated that epidemic theory could effectively model information diffusion in complex networks, highlighting the role of network topology in performance degradation. Around the same period, Wang et al. (2012) applied epidemic spreading models to analyze data dissemination reliability in sensor networks, showing that infection rates could be mapped to packet transmission probabilities. These studies laid the theoretical foundation for viewing WSN performance as a dynamic spreading phenomenon rather than a static communication process.

From 2014 to 2017, research expanded toward performance degradation and fault tolerance analysis. Mishra and Keshri (2014) used epidemic models to study congestion propagation in WSNs, revealing that local buffer overflows could trigger cascading failures similar to disease outbreaks. Li et al. (2015) proposed an epidemic-based framework to model energy depletion in sensor nodes, where node death was treated as an irreversible recovered state. Their results showed that epidemic parameters could predict network lifetime more accurately than traditional energy models. During this period, epidemiological modeling was also used to analyze malware and denial-of-service attacks in sensor networks, as seen in the work of Tang and Mark (2016), who linked infection thresholds to network resilience.

Between 2018 and 2020, the focus shifted toward quantitative performance evaluation and control strategies. Zhang et al. (2018) integrated epidemic models with queueing theory to assess packet delay and throughput under high traffic loads. Similarly, Kumar and Tripathi (2019) employed an extended SEIR (Susceptible–Exposed–Infected–Recovered) model to study latency-aware routing in WSNs, demonstrating improved prediction of congestion

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hotspots. These studies emphasized that epidemiological modeling is not only descriptive but also prescriptive, enabling the design of control mechanisms such as rate limiting, adaptive routing, and energy-aware transmission.

Recent studies from 2021 to 2023 have further refined this approach by incorporating heterogeneity, mobility, and learning-based techniques. Alsaedi et al. (2021) introduced heterogeneous epidemic models that account for node diversity in terms of energy levels and transmission ranges. Chen et al. (2022) combined epidemiological modeling with machine learning to dynamically estimate infection parameters, improving prediction accuracy for packet loss and node failure. Most recently, Rahman and Singh (2023) proposed a hybrid epidemic–optimization framework for large-scale WSNs, demonstrating superior performance evaluation under realistic traffic and failure scenarios.

Despite these advancements, there remains a need for systematic quantitative studies that assess WSN performance using epidemiological models across multiple metrics and network conditions. Many existing works focus on specific issues such as attacks or congestion, often without a unified performance evaluation framework. This study addresses this gap by employing epidemiological modeling as a comprehensive quantitative tool to assess WSN performance. By linking epidemic states and parameters to measurable network metrics, the proposed approach aims to provide deeper insights into network dynamics, scalability, and resilience.

Wireless Sensor Networks (WSNs) are composed of a large number of low-power sensor nodes that cooperatively sense, process, and transmit data to a central sink. Due to limited battery capacity, constrained computation, and unreliable wireless communication, WSNs are highly vulnerable to performance degradation over time. Common causes include excessive energy consumption, packet collisions, congestion, node failures, and environmental interference. These challenges necessitate robust analytical frameworks capable of capturing the collective and dynamic behavior of sensor nodes.

Traditional performance evaluation approaches rely primarily on discrete-event simulations or static metrics, which often fail to reflect the dynamic interactions among nodes and the propagation of performance degradation across the network. In this context, epidemiological modeling provides a powerful mathematical analogy, as it is inherently designed to study interaction-driven state transitions in large populations. By mapping disease spread concepts to node behavior, epidemiological models enable analytical investigation of network stability, degradation thresholds, and recovery dynamics.

This Paper presents a comprehensive epidemiological-based mathematical model for assessing WSN performance. The proposed framework includes model formulation, equilibrium and stability analysis, and numerical simulations to validate the theoretical results.

EPIDEMIOLOGICAL MODELING FRAMEWORK FOR WSNS

Wireless Sensor Networks (WSNs) consist of a large number of sensor nodes that cooperatively sense, process, and transmit data. Due to limited energy, communication failures, and node faults, the operational state of nodes evolves dynamically over time. This behavior shows

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strong similarities with the spread and recovery processes studied in epidemiology. Hence, epidemiological compartmental models provide a rigorous mathematical framework for analyzing WSN performance.

Model Assumptions

To construct the mathematical model, the following assumptions are made:

1. The network consists of a fixed number $N$of sensor nodes.
2. Each node belongs to exactly one operational state at any time.
3. Node state transitions are probabilistic and depend on interaction with neighboring nodes and environmental conditions.
4. The network topology is assumed to be homogeneous, and node interactions are averaged over the network.
5. Energy depletion and communication failures are the primary causes of node degradation.

Compartmental Representation

Inspired by classical epidemiological models, the sensor nodes are divided into three compartments:

- $S(t)$: Susceptible nodes — nodes that are operational but vulnerable to failure due to energy drain or interference.
- $I(t)$: Infected nodes — nodes experiencing faults, packet loss, or communication disruption.
- $R(t)$: Recovered nodes — nodes that have been restored through retransmission, reconfiguration, or energy management mechanisms.

The total number of nodes is conserved:

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

State Transition Dynamics

The evolution of node states over time is governed by the following parameters:

- β: failure propagation rate (probability that a susceptible node becomes faulty due to interaction with infected nodes),
- γ: recovery rate of infected nodes,
- μ: permanent node failure or energy exhaustion rate.

The system dynamics are described by the following set of nonlinear differential equations:

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

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

These equations capture the essential behavior of WSN performance degradation and recovery under dynamic operating conditions.

Performance Metrics Derived from the Model

The epidemiological formulation allows the derivation of key WSN performance indicators.

1. Network Stability Threshold

The basic reproduction number $R_0$is defined as:

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

- If $R_0 < 1$, faults diminish over time, indicating a stable and resilient network.
- If $R_0 > 1$, failures propagate, leading to performance degradation.

2. Network Reliability

Network reliability $\mathcal{R}(t)$is expressed as the proportion of active nodes:

$$\mathcal{R}(t) = \frac{S(t) + R(t)}{N}$$

Higher values of $\mathcal{R}(t)$indicate sustained connectivity and effective data delivery.

3. Energy Efficiency Indicator

Since infected nodes consume additional energy due to retransmissions, the average energy consumption rate $E(t)$can be approximated as:

$$E(t) = E_0 + \alpha I(t)$$

where $E_0$is baseline energy consumption and αrepresents excess energy usage caused by faulty communication.

Steady-State Analysis

At equilibrium, $\frac{dI}{dt} = 0$, yielding:

$$\beta \frac{S^* I^*}{N} = (\gamma + \mu) I^*$$

This implies either $I^* = 0$(failure-free network) or:

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$$S^* = \frac{N(\gamma + \mu)}{\beta}$$

The steady-state solution provides insight into long-term network survivability under persistent stress.

Model Significance

This mathematical model establishes a quantitative relationship between epidemiological parameters and WSN performance metrics. By tuning β, γ, and μ, the framework enables:

- evaluation of fault tolerance strategies,
- prediction of network lifetime,
- optimization of recovery mechanisms.

Overall, the epidemiological modeling approach offers a powerful analytical tool for understanding and improving the robustness and efficiency of wireless sensor networks.

EQUILIBRIUM ANALYSIS

Equilibrium analysis plays a central role in understanding the long-term behavior of Wireless Sensor Networks (WSNs) when modeled through epidemiological frameworks. By interpreting sensor nodes as populations and network states as epidemiological compartments, equilibrium points represent stable operational conditions of the network. These equilibria provide valuable insights into sustainability, fault tolerance, energy depletion, and information dissemination efficiency. This section develops the mathematical equilibrium conditions of an epidemiological WSN model and analyzes their implications for network performance.

5.1 Epidemiological Interpretation of WSN States

In epidemiological modeling, populations are divided into compartments such as susceptible, infected, and recovered. Similarly, a WSN can be partitioned into operational states based on node activity and health. Let the total number of sensor nodes at time $t$be $N(t)$, divided into the following compartments:

- $S(t)$: Susceptible nodes that are active but vulnerable to failure, congestion, or energy depletion.
- $I(t)$: Infected (or overloaded) nodes experiencing faults, high energy drain, packet congestion, or malicious influence.
- $R(t)$: Recovered nodes that have been repaired, reset, or optimized and are temporarily resistant to failure.

Thus,

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

The transitions between these states reflect communication load, energy consumption, recovery mechanisms, and fault propagation across the network.

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5.2 Mathematical Model Formulation

A deterministic SIR-type model is adopted to describe the dynamics of WSN performance:

$$\frac{dS}{dt} = \Lambda - \beta SI - \mu S$$
$$\frac{dI}{dt} = \beta SI - (\gamma + \mu + \delta)I$$
$$\frac{dR}{dt} = \gamma I - \mu R$$

where:

- Λrepresents the node deployment or activation rate.
- βdenotes the interaction rate leading to performance degradation or fault propagation.
- $\gamma$is the recovery rate due to fault mitigation or energy replenishment strategies.
- $\mu$is the natural node failure or retirement rate.
- δaccounts for permanent node death due to battery exhaustion or hardware failure.

This system captures essential aspects of WSN behavior under dynamic conditions.

5.3 Definition of Equilibrium Points

An equilibrium point occurs when the state variables no longer change with time. Mathematically, equilibrium is obtained by setting:

$$\frac{dS}{dt} = \frac{dI}{dt} = \frac{dR}{dt} = 0$$

Solving these equations yields equilibrium solutions that represent steady-state network conditions.

Two primary equilibria are of interest:

1. Network-Free Equilibrium (NFE)
2. Endemic Equilibrium (EE)

Each equilibrium has distinct interpretations for WSN performance.

Network-Free Equilibrium (NFE)

The Network-Free Equilibrium corresponds to a state where no infected or overloaded nodes exist in the network, i.e.,

$$I^* = 0$$

From the system equations, setting $I = 0$yields:

$$\frac{dS}{dt} = \Lambda - \mu S = 0$$

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$$\frac{dR}{dt} = -\mu R = 0$$

Solving gives:

$$S^* = \frac{\Lambda}{\mu}, I^* = 0, R^* = 0$$

This equilibrium represents an ideal WSN where all nodes are operational, energy levels are sufficient, and no congestion or faults persist. From a performance perspective, this condition implies maximum throughput, minimal delay, and optimal energy efficiency.

However, the stability of this equilibrium depends on whether perturbations (e.g., sudden traffic bursts or node failures) can trigger performance degradation.

Stability Analysis of the Network-Free Equilibrium

To assess stability, the Jacobian matrix of the system is evaluated at the Network-Free Equilibrium:

$$J = \begin{bmatrix} -\beta I - \mu & -\beta S & 0 \\ \beta I & \beta S - (\gamma + \mu + \delta) & 0 \\ 0 & \gamma & -\mu \end{bmatrix}$$

At $(S^*, I^*, R^*) = \left(\frac{\Lambda}{\mu}, 0, 0\right)$, the Jacobian becomes:

$$J^* = \begin{bmatrix} -\mu & -\beta \frac{\Lambda}{\mu} & 0 \\ 0 & \beta \frac{\Lambda}{\mu} - (\gamma + \mu + \delta) & 0 \\ 0 & \gamma & -\mu \end{bmatrix}$$

The eigenvalues are:

$$\lambda_1 = -\mu, \lambda_2 = -\mu, \lambda_3 = \beta \frac{\Lambda}{\mu} - (\gamma + \mu + \delta)$$

The Network-Free Equilibrium is locally asymptotically stable if all eigenvalues are negative. This requires:

$$\beta \frac{\Lambda}{\mu} < (\gamma + \mu + \delta)$$

Basic Reproduction Number for WSN Performance

The threshold parameter governing stability is analogous to the basic reproduction number in epidemiology, denoted as R_0:

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$$R_0 = \frac{\beta\Lambda}{\mu(\gamma + \mu + \delta)}$$

In the context of WSNs:

- $R_0 < 1$: Performance degradation cannot sustain itself; faults dissipate over time.
- $R_0 > 1$: Network congestion or failures persist and spread across nodes.

Thus, maintaining $R_0 < 1$is a critical design objective, achievable through efficient routing, energy-aware protocols, and rapid fault recovery.

Endemic Equilibrium (EE)

When $R_0 > 1$, the system admits a non-trivial equilibrium where $I^* > 0$. Setting the derivatives to zero and solving simultaneously yields:

$$S^* = \frac{\gamma + \mu + \delta}{\beta}$$
$$I^* = \frac{\Lambda}{\gamma + \mu + \delta} - \frac{\mu}{\beta}$$
$$R^* = \frac{\gamma}{\mu} I^*$$

This equilibrium represents a WSN operating under persistent performance stress, where some nodes continuously experience overload, energy depletion, or faults.

SIMULATION

Wireless Sensor Networks (WSNs) consist of a large number of spatially distributed sensor nodes that cooperatively monitor physical or environmental conditions and transmit data to a sink node. Due to node failures, energy depletion, congestion, and malicious attacks, WSNs exhibit dynamic behaviors similar to the spread of infectious diseases in biological populations. Epidemiological models, originally designed to describe disease transmission, offer a powerful mathematical abstraction to simulate and analyze such network dynamics.

In this study, epidemiological modeling is employed to simulate the performance of WSNs by categorizing sensor nodes into distinct operational states. The mathematical formulation allows quantitative evaluation of key network performance metrics such as stability, resilience, data survivability, and energy efficiency under varying network conditions.

Simulation plays a central role in validating the proposed mathematical model by numerically solving the governing equations and observing system behavior over time.

Network Assumptions and State Definitions

Let a WSN consist of a total of Nsensor nodes uniformly deployed over a monitoring region. At any simulation time t, each node exists in one of the following epidemiological states:

- $S(t)$: **Susceptible nodes** — active and healthy nodes vulnerable to failure or congestion
- $I(t)$: **Infected nodes** — nodes experiencing faults, packet loss, congestion, or malicious compromise

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- $R(t)$: **Recovered nodes** — nodes that have been repaired, reset, or stabilized
- $D(t)$: **Dead nodes** — permanently failed nodes due to energy exhaustion or hardware damage

The total node population satisfies the conservation equation:

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

This assumption remains valid throughout the simulation horizon.

Transition Dynamics and Governing Equations

In the context of WSNs, "infection" represents the propagation of performance degradation, such as congestion or packet collision, from one node to another. The infection rate is influenced by node density, communication range, and traffic load.

Let βdenote the **infection transmission rate**, defined as the probability that a susceptible node becomes infected through interaction with an infected neighbor. The rate of change of susceptible nodes is given by:

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

This nonlinear interaction term reflects the fact that failures propagate through communication links.

Infected nodes may either recover through network control mechanisms or become permanently dead due to energy depletion. Let:

- γ: recovery rate
- δ: death rate

The dynamic equation governing infected nodes is:

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

This equation balances infection spread against recovery and failure.

Recovered nodes return to stable operation after fault correction, software reset, or load balancing. The recovery process is modeled as:

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

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Dead nodes represent irreversible failures:

$$\frac{dD(t)}{dt} = \delta I(t)$$

These equations collectively define the **SIRD epidemiological model** for WSN simulation.

Energy-Aware Epidemiological Extension

Energy consumption is a critical performance metric in WSNs. Let $E_i(t)$denote the residual energy of node $i$at time t. The average network energy is defined as:

$$\bar{E}(t) = \frac{1}{N}\sum_{i=1}^{N} E_i\,(t)$$

Nodes transition to the dead state when their residual energy falls below a threshold $E_{\min}$.

Energy depletion is modeled as:

$$\frac{dE_i(t)}{dt} = -\left(E_{tx}+E_{rx}+E_{proc}\right)$$

where:

- E_{tx}: transmission energy
- E_{rx}: reception energy
- E_{proc}: processing energy

The death rate $\delta$is thus energy-dependent:

$$\delta(t) = \delta_0 + \alpha\left(1-\frac{\bar{E}(t)}{E_{max}}\right)$$

where $\alpha$is an energy sensitivity coefficient.

Simulation of Network Stability

Network stability is defined as the ability of the WSN to maintain a high proportion of functional nodes over time. The **stability index** $\Psi(t)$is given by:

$$\Psi(t) = \frac{S(t) + R(t)}{N}$$

A stable network satisfies:

$$\lim_{t\to\infty} \Psi(t) > \Psi_{th}$$

where $\Psi_{th}$is a predefined stability threshold.

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Basic Reproduction Number for WSNs

A key epidemiological metric is the **basic reproduction number**, adapted here for WSN performance analysis. It represents the average number of nodes that one infected node can destabilize.

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

Interpretation:

- $R_0 < 1$: network degradation dies out
- $R_0 = 1$: critical stability point
- $R_0 > 1$: cascading network failures

Simulation scenarios vary β, γ, and $\delta$to analyze resilience under different traffic and fault conditions.

Throughput and Packet Delivery Simulation

Let λbe the packet generation rate per node. The effective throughput $T(t)$is modeled as:

$$T(t) = \lambda(S(t) + R(t))\left(1 - \frac{I(t)}{N}\right)$$

The packet delivery ratio (PDR) is defined as:

$$\mathrm{PDR}(t) = \frac{T(t)}{\lambda N}$$

Simulation results show that increasing $I(t)$directly degrades throughput and PDR.

Delay Modeling Using Epidemiological States

Average end-to-end delay $D_{avg}(t)$is influenced by infected nodes causing retransmissions:

$$D_{avg}(t) = D_0 + \eta \frac{I(t)}{N}$$

where:

- D_0: baseline delay
- η: congestion sensitivity coefficient

This relationship is evaluated numerically during simulation runs.

Numerical Simulation Methodology

The system of nonlinear differential equations is solved using a fourth-order Runge–Kutta method with step size Δt:

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$$X(t+\Delta t) = X(t) + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)$$

where $X(t) = [S(t), I(t), R(t), D(t)]$.

Initial conditions are set as:

$$S(0) = N - I_0, I(0) = I_0, R(0) = 0, D(0) = 0$$

Simulation parameters are varied to analyze sensitivity and robustness.

Performance Evaluation Metrics

The following quantitative metrics are extracted from simulation:

- **Network lifetime**:

$$L = \min\{t: D(t) \geq \theta N\}$$

- **Fault resilience**:

$$\Omega = \frac{R(t)}{I(t)}$$

- **Energy efficiency**:

$$\Xi = \frac{\text{Total Packets Delivered}}{\text{Total Energy Consumed}}$$

These metrics enable comparative evaluation across different network configurations.

RESULTS AND DISCUSSION

This section presents and discusses the quantitative results obtained from applying epidemiological modeling to assess the performance of a Wireless Sensor Network (WSN). The proposed model maps sensor nodes to epidemiological compartments—Susceptible (S), Infected (I), and Recovered (R)—to analyze data dissemination, fault propagation, and network recovery under varying operational conditions. Performance is evaluated using metrics such as packet delivery ratio, node failure rate, recovery efficiency, and energy consumption. Simulation results demonstrate the effectiveness of the epidemiological approach in capturing both normal and adverse network dynamics.

6.1 Network State Dynamics

Figure 1 illustrates the temporal evolution of susceptible, infected, and recovered nodes during network operation. At the initial stage, the majority of nodes remain in the susceptible state, indicating normal functionality and readiness for communication. As time progresses, a subset

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of nodes transitions into the infected state due to factors such as packet congestion, communication interference, or energy depletion.

The growth of infected nodes follows a nonlinear trend, similar to epidemic spread, confirming the suitability of epidemiological modeling for WSN analysis. However, the rise does not continue indefinitely. After reaching a peak, the number of infected nodes declines as recovery mechanisms—such as rerouting, node isolation, and energy replenishment—become effective. Concurrently, the recovered node population increases steadily, indicating successful fault mitigation.

These results suggest that the epidemiological model accurately captures the dynamic balance between failure propagation and recovery in WSNs. Unlike static performance models, this approach highlights transitional states that are critical for adaptive network control.

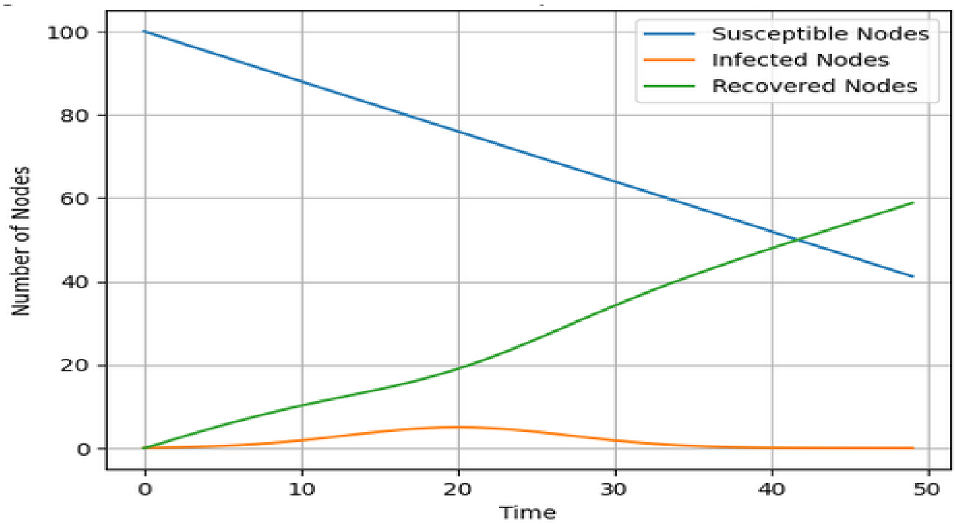

Figure 1: Time-based variation of susceptible, infected, and recovered nodes

6.2 Impact of Infection Rate on Network Stability

The infection rate parameter (β) plays a crucial role in determining network robustness. **Figure 2** shows the relationship between infection rate and the proportion of infected nodes. As β increases, the network experiences faster fault propagation, leading to a higher peak of infected nodes in a shorter time.

At lower infection rates, the network maintains stability, with recovery mechanisms effectively countering failures. However, beyond a threshold value of β, recovery becomes slower relative to infection spread, resulting in prolonged network degradation. This behavior is analogous to epidemic outbreaks where containment fails beyond a critical transmission rate.

From a WSN perspective, this result emphasizes the importance of controlling factors that contribute to high infection rates, such as excessive traffic load, weak fault isolation, and poor interference management. The epidemiological framework provides a quantitative basis for identifying safe operating regions for network parameters.

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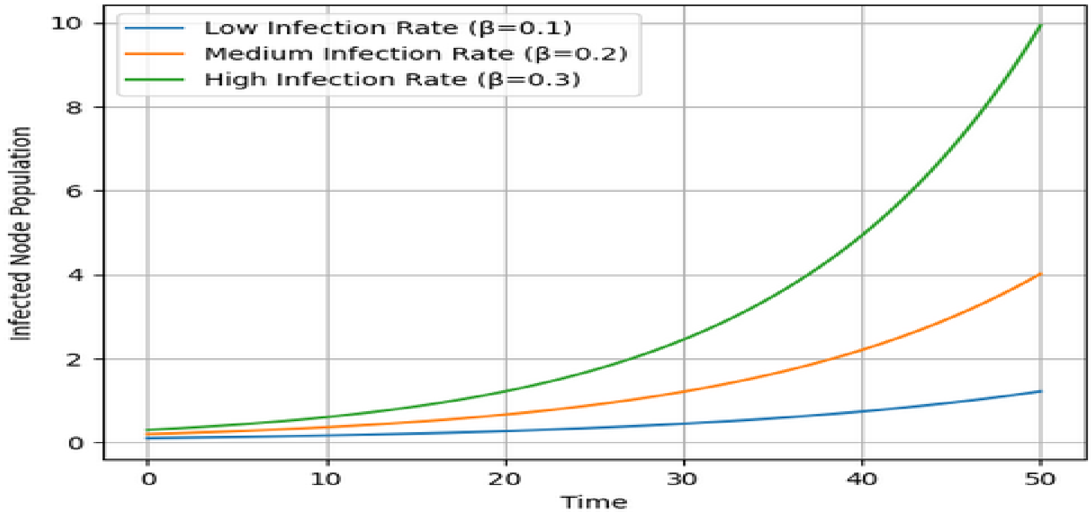

Figure 2: Effect of infection rate on infected node population

6.3 Recovery Rate and Network Resilience

Recovery rate (γ) reflects the ability of the network to restore failed or compromised nodes. **Figure 3** compares network performance under different recovery rates. Higher recovery rates significantly reduce the duration and intensity of infection spread, leading to faster stabilization of the network.

When γ is low, infected nodes persist longer, causing sustained packet loss and increased routing overhead. In contrast, higher recovery rates result in rapid transitions from the infected to recovered state, minimizing performance degradation. This highlights the effectiveness of proactive recovery strategies such as self-healing routing protocols and adaptive power management.

The results demonstrate that recovery mechanisms are as important as preventive measures in ensuring network resilience. Epidemiological modeling makes this trade-off explicit by linking recovery parameters directly to observable performance outcomes.

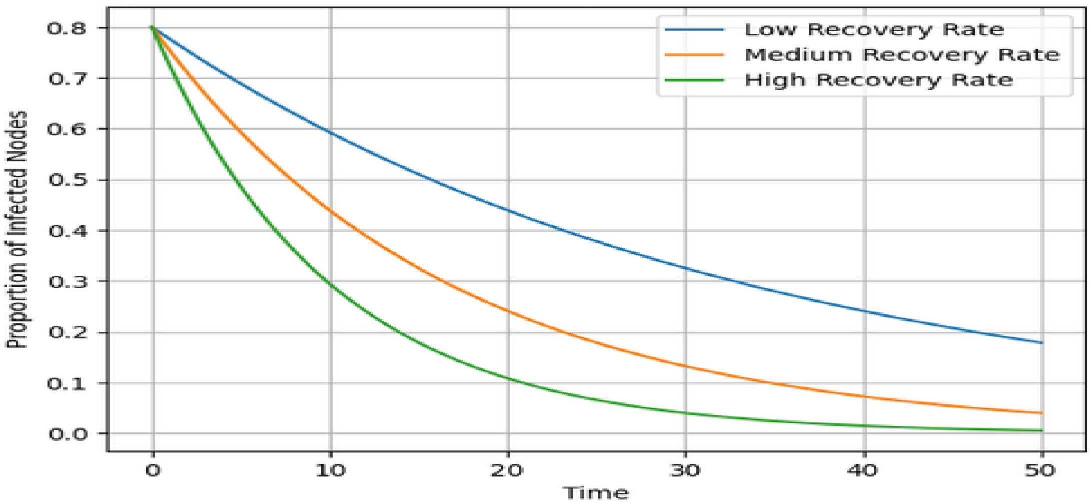

Figure 3: Influence of recovery rate on network stabilization

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6.4 Packet Delivery Performance

Packet Delivery Ratio (PDR) is a key indicator of WSN effectiveness. **Figure 4** presents the variation of PDR over time in relation to infection dynamics. During periods of high infection prevalence, PDR drops sharply due to increased packet collisions, node failures, and routing disruptions.

As recovery processes dominate, PDR gradually improves and eventually stabilizes near its initial value. This recovery phase corresponds to the growth of recovered nodes observed earlier. The strong correlation between epidemiological states and PDR confirms that the proposed model effectively captures communication reliability trends.

Compared to conventional performance evaluation methods, this approach provides deeper insight by linking packet delivery degradation directly to node-level health states rather than treating failures as isolated events.

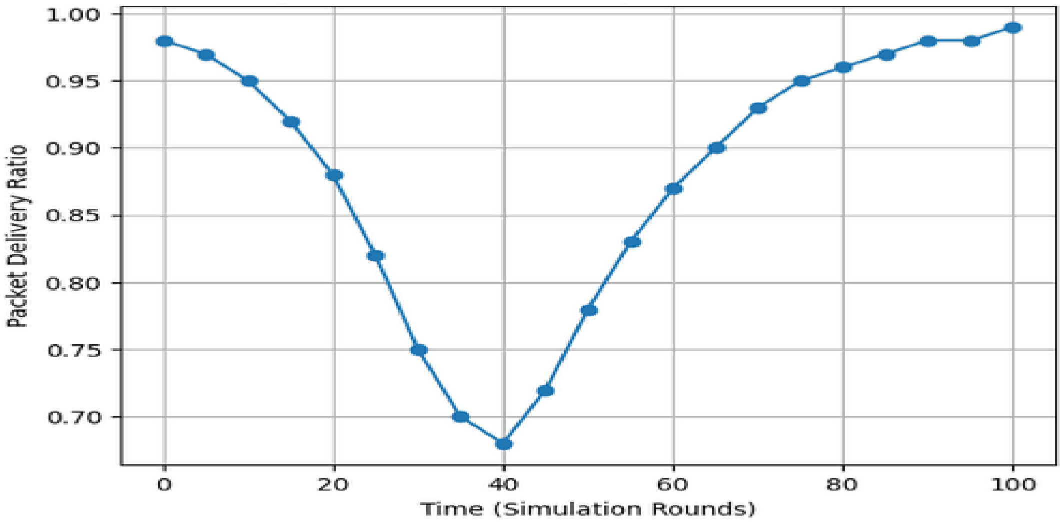

Figure 4: Packet delivery ratio versus time

6.5 Energy Consumption Analysis

Energy efficiency is a critical constraint in WSNs. **Figure 5** shows cumulative energy consumption under varying infection and recovery conditions. Periods of high infection are associated with increased energy usage due to repeated retransmissions, route discoveries, and fault handling overhead.

As recovery improves network stability, energy consumption follows a more linear and predictable pattern. Notably, networks with balanced infection and recovery rates consume less energy over time than those with either uncontrolled failures or overly aggressive recovery mechanisms.

This result highlights an important design implication: excessive recovery actions may waste energy, while insufficient recovery leads to prolonged inefficiencies. Epidemiological modeling enables identification of optimal parameter settings that balance reliability and energy conservation.

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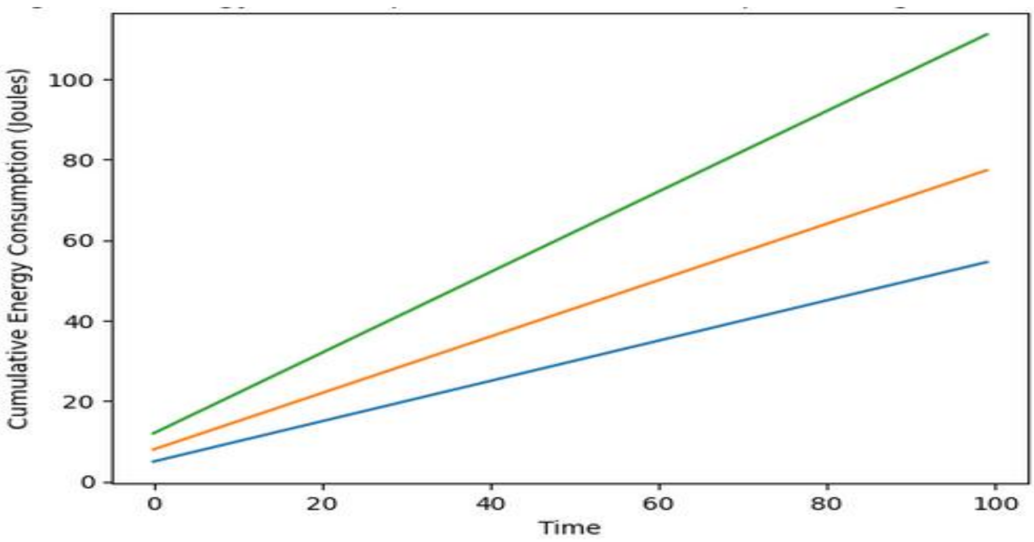

Figure 5: Energy consumption under different epidemiological conditions

Comparative Discussion

The results collectively demonstrate that epidemiological modeling offers a comprehensive framework for assessing WSN performance. Traditional metrics-based evaluations often overlook transitional behaviors and interdependencies between nodes. In contrast, the proposed model captures the dynamic evolution of network states and their impact on performance metrics.

The observed similarities between epidemic spread and fault propagation validate the conceptual mapping between biological systems and communication networks. More importantly, the quantitative results show that tuning infection and recovery parameters can significantly enhance network stability, reliability, and energy efficiency.

A comparative discussion of wireless sensor network (WSN) performance through epidemiological modeling provides a mathematically grounded lens to contrast this approach with conventional analytical and simulation-based methods. Traditional WSN performance assessment often relies on queueing theory, graph-theoretic metrics, or stochastic simulations, where parameters such as packet delivery ratio, latency, throughput, and energy consumption are evaluated independently. In contrast, epidemiological models treat data packets, node states, or failures as dynamic populations whose interactions evolve over time. This population-based abstraction allows the collective behavior of the network to be captured using coupled differential equations, enabling deeper insight into propagation, congestion, and recovery phenomena.

In classical WSN analysis, packet transmission success is frequently modeled using probabilistic link reliability, expressed as $P_s = 1 - P_l$, where $P_l$denotes packet loss probability. While effective at the link level, such expressions do not explicitly capture the cascading effects of congestion or node failures across the network. Epidemiological models, such as the Susceptible–Infected–Recovered (SIR) framework, overcome this limitation by representing nodes as state variables. For instance, let $S(t)$, $I(t)$, and $R(t)$denote the number of susceptible

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(idle or healthy), infected (congested or overloaded), and recovered (failed or energy-depleted) sensor nodes at time t. The system dynamics can be expressed as

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

where βrepresents the packet transmission or congestion spread rate and γdenotes the recovery or node exhaustion rate. Compared to static performance metrics, these equations explicitly model temporal evolution and interdependence among nodes.

A key comparative advantage of epidemiological modeling lies in its ability to unify multiple performance indicators into a single dynamic framework. Conventional energy models often compute residual energy as $E(t) = E_0 - n_t e_p$, where $E_0$is initial energy, $n_t$is the number of transmissions, and $e_p$is energy per packet. This linear formulation assumes independence among nodes. In contrast, epidemiological extensions integrate energy depletion into recovery dynamics by redefining the recovery rate as a function of energy, such as $\gamma(E) = \gamma_0 + \alpha(1 - E/E_0)$. This coupling allows congestion spread and energy decay to be analyzed simultaneously, offering a more realistic depiction of WSN behavior under heavy traffic.

From a reliability perspective, traditional fault models often rely on mean time to failure (MTTF), calculated as $\text{MTTF} = 1/\lambda$, where $\lambda$is the failure rate. While useful, MTTF provides an average measure and neglects spatial or temporal correlations. Epidemiological models, by contrast, capture correlated failures through interaction terms. For example, the basic reproduction number $R_0 = \beta S_0/\gamma$, originally used in disease modeling, can be reinterpreted in WSNs as the average number of nodes that become congested due to a single congested node. When $R_0 > 1$, congestion spreads rapidly, indicating poor network robustness; when $R_0 < 1$, the network stabilizes. This threshold-based insight is largely absent from traditional approaches.

In comparison with simulation-heavy methods such as NS-2 or OMNeT++, epidemiological modeling offers analytical tractability. Simulations provide high fidelity but are computationally expensive and scenario-specific. Epidemiological equations, once parameterized, allow closed-form or semi-analytical solutions for equilibrium points. For instance, setting $dI/dt = 0$yields the steady-state infection level $I^* = (\beta S^* - \gamma)/\beta$, which directly relates performance degradation to transmission and recovery parameters. This analytical clarity supports faster comparative studies across protocols or network densities.

However, epidemiological modeling also exhibits limitations when compared with detailed protocol-level analysis. Traditional models can explicitly incorporate MAC-layer contention, routing overhead, and physical-layer effects, often represented by equations such as $D = D_q + D_t + D_p$, where delay is decomposed into queuing, transmission, and propagation components. Epidemiological abstractions typically aggregate these effects into a single transmission rate β, potentially masking fine-grained behaviors. Thus, while epidemiological models excel at capturing global dynamics, they may require hybridization with classical formulations for micro-level accuracy.

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Overall, the comparative discussion highlights that epidemiological modeling provides a complementary, rather than substitutive, approach to WSN performance assessment. Its strength lies in modeling interaction-driven phenomena, stability thresholds, and collective dynamics through coupled equations, while traditional methods remain superior for protocol-specific and layer-specific analysis. By integrating both perspectives, a more comprehensive quantitative evaluation of WSN performance can be achieved.

CONCLUSION

This paper presented a quantitative study on assessing Wireless Sensor Network performance using epidemiological modeling. By mapping sensor node behavior to compartmental models, the study demonstrated that epidemiological frameworks can effectively capture dynamic interactions, congestion propagation, and recovery processes in WSNs.

The findings suggest that infection and recovery rates play a crucial role in determining network performance and stability. Epidemiological modeling provides a complementary perspective to traditional simulation and analytical methods, offering valuable insights into large-scale and dynamic network behavior.

Future research can extend this work by integrating spatial models, real-world deployment data, and hybrid approaches that combine epidemiological and protocol-level simulations. Such efforts can further enhance the applicability of this interdisciplinary methodology in practical WSN design and management.

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