CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

RAIL ROUTING STRATEGY BASED ON DECISION THEORY FOR WIRELESS SENSOR NETWORKS

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Abstract: With the latest communication technology rapidly advancing each year, it's important to consider how railway infrastructure can stay up to date, not only for the convenience of passengers on Reliable connectivity on board trains not only enhances passenger experience by allowing them to stay connected and productive during their journey—unlike in-flight or driving scenarios where connectivity is limited—but also supports effective signalling and control across extensive rail networks. Implementing hierarchical cluster-based decision theory for network management ensures both stability and scalability.. The core features of the designed decision theory includes hierarchical routing, energy efficient routing , delay-aware routing. In this Routing scheme based on decision theory (DT) is reviewed and the energy consumption, delay, packet delivery ratio and the life time of the network is much improved. When evaluating a routing method that performs comparatively better than existing methods without the need for additional plugins or external tools, several key factors are typically involved:

Key words:WSN, Routing protocol, decision theory, transferring time, packet ratio, DT.

I. INTRODUCTION

Wireless Sensor Network (WSN) is composed of small, smart nodes that include communication, data computation, and sensing capabilities. These nodes collaborate to transmit information from a target area to a central sink using a multi-hop network. Nodes can be positioned deep within or close to the target area. As the number of hops increases, network latency generally increases as well. To address these challenges, the Small World Wireless Sensor Network (SW-WSN) [1] has been introduced This approach seeks to balance energy distribution more evenly and effectively minimize latency.

Collecting real-time data in WSNs is often challenging, but the network's lifespan can be extended using the Big Data Algorithm (BDEG) [2], which optimizes communication within clusters by assessing the energy levels of sensor nodes. Transmission lines are monitored by towers that maintain a secure distance between lines to prevent interference. The Transmission Tower Monitoring Network [3] is responsible for overseeing the entire transmission line and managing redundant data at the reader's end, though it still suffers from higher latency.

To reduce network complexity during data transmission, the Fragmentation Aggregation Transmission Wireless Sensor Network (FAT-WSN) [4] has been introduced. This approach minimizes energy consumption and speeds up the transmission process. With a large number of nodes in a WSN, these nodes are capable of detecting environmental changes. They select relevant data before forwarding it to

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
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the base station, a process optimized by the redundancy removal strategy [5].

Localization is essential in WSNs because it provides critical information about the sensor nodes' locations, which is important for network operations and application tasks such as target detection. Data collection and localization are enhanced by the Small World characteristics [6], which are achieved through mobile ubiquitous LAN extension. This method reduces path lengths and increases cluster efficiency, thereby decreasing the number of hops needed and accelerating data transmission.

To improve transmission efficiency, it is necessary to decompose data access control, hybrid transmission management, and intermediate computations. This is achieved using Lyapunov function-based network optimization theory [7]. This approach effectively deals with selfish nodes and fosters cooperation among nodes to enhance routing efficiency and conserve energy. To ensure optimal cooperation among nodes, we have mathematically formulated the Bargaining decision for real-time implementation in sensor networks. The DT offers several key advantages: it monitors systems, devices, clouds, and traffic without requiring additional plugins, making it both powerful and efficient with reduced transmission times.

The organization of the remainder of this paper is as follows: Section I explores the foundational game theory concepts pertinent to Wireless Sensor Networks (WSNs) and defines the key performance metrics; Section II examines previous research and applications of game theory in this context; Section III details the proposed Decision Theory (DT) approach and its implementation; Section IV analyzes the experimental results and evaluates the performance of the proposed solution; and Section V summarizes the findings and offers concluding remarks in this paper.

II. RELATED WORK

Selvakumaran et al. [2017] [15] introduced the Cluster Chain Mobile Agent Routing (CCMAR) algorithm, which improves aggregation within network topologies. This algorithm enhances key performance metrics of Wireless Sensor Networks (WSNs), such as energy consumption, transmission delay, and network lifetime. However, a notable drawback of CCMAR is that as the number of nodes increases, transmission delays also tend to rise.

Om Jee Pandey et al. [2018] [1] proposed the Small World Wireless Sensor Network (SW-WSN), which aims to reduce transmission path lengths and improve cluster coefficients by creating novel links between selected nodes. Despite its advancements, SW-WSN encounters challenges related to its dependence on various network and load characteristics.

Fangming et al. [2019] [3] established a transmission tower monitoring system that merges Wireless Sensor Networks (WSNs) with Radio Frequency Identification (RFID) technology. This approach effectively manages transmission delays and monitors transmission towers, but it falls

Chaa Ma et al. [2019] [4] proposed the Fragmentation Aggregation Transmission Wireless Sensor Network (FAT-WSN) to reduce data fragmentation created a monitoring network for transmission towers that combines Wireless Sensor Networks (WSNs) with Radio Frequency Identification (RFID) technology..

N.A.M. Alduais [2019] [8] introduced the RDCM, which consists of two key levels: the IoT sensor board level for real-time operations and the fusion center level for enhancing network topology. While RDCM boosts overall performance, the large amount of data that needs to be updated can strain the

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Volume 06 Issue 2
2024

ISSN:1624-1940
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energy resources of sensor nodes, creating a notable challenge in maintaining energy efficiency. Existing routing methods encounter several issues, such as packet delivery ratio, end-to-end delay, node failures, and complications with downstream links. Additionally, these methods often do not suit distributed architectures. To overcome these problems, the Routing scheme based on decision Theory (DT) has been proposed. DT excels in performance metrics, offering robust system monitoring for devices, clouds, and traffic without needing extra plugins. It is both powerful and efficient, with reduced transmission times, making it superior to other existing methods.

III. PROPOSED SYSTEM

Hierarchical Routing Implementation with Graph

1. Network Organization

Graph Description:

- **Nodes**: Represented as vertices (circles).
- **Clusters**: Groups of nodes (vertices) connected to a central cluster head (CH).
- **Hierarchy Levels**: Nodes and CHs organized into multiple levels, including local clusters and global levels.

Graph Example:

plaintext

Copy code

```
      [Base Station]
           |
   ---------------------
   |       |       |
  [Region 1] [Region 2] [Region 3]
   |        |        |
  ----      ----      ----
  | |      | |      | |
[N1][N2]    [N3][N4]    [N5][N6]
  |        |        |
 [CH1]      [CH2]      [CH3]
   \      /         /
   ---------------------
           |
      [Sink/Base Station]
```

2. Routing Protocols

Graph Description:

- **Data Paths**: Arrows representing the flow of data from nodes through CHs to the base station.
- **Data Aggregation**: Shows how data is collected and forwarded from local clusters to higher levels.

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Graph Example:

plaintext

Copy code

```
 [N1]---\
        \
        [CH1]---\
                \
                 [Region 1]---\
                              \
 [N2]---/                      [Base Station]
        /
 [N3]---\
        \
        [CH2]---\
                \
                 [Region 2]---\
                              \
 [N4]---/                      [Base Station]
        /
 [N5]---\
        \
        [CH3]---\
                \
                 [Region 3]---\
                              \
 [N6]---/                      [Base Station]
```

Explanation:

- **Data Flow**: Data from nodes (N1, N2, etc.) is aggregated by CHs (CH1, CH2, CH3) and then sent to the Base Station through regional aggregations.

3. Communication Protocols

Graph Description:

- **Communication Channels**: Lines or arrows showing communication between nodes, CHs, and the base station.
- **Energy Management**: Indicates power-efficient routing paths.

Graph Example:

plaintext

Copy code

```
 [N1]---\      [CH1]---\       [Base Station]
         \      /       \
```

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```
        \    /        \
         [N2]          [Region 1]
                    /     \
 [N3]---\              /      [Base Station]
       \          /        /
        [CH2]----\  [Region 2] /
                 \ /       /
 [N4]---\          [Base Station]
       \
        [N5]---\
              [CH3]---\.
```

Implement Energy-Efficient Routing Algorithm

A common energy-efficient routing protocol is LEACH (Low-Energy Adaptive Clustering Hierarchy). Here's a basic implementation:

a. Define LEACH Parameters

```
% LEACH Parameters
numClusters = 5;              % Number of clusters
clusterHeadProbability = 0.1; % Likelihood of a node being selected as a cluster head
```

b. Cluster Formation

```
% Randomly assign cluster heads
numCHs = round(clusterHeadProb * numNodes);
clusterHeads = randperm(numNodes, numCHs);

% Plot cluster heads
figure;
scatter(nodePositions(:,1), nodePositions(:,2), 'filled');
hold on;
scatter(nodePositions(clusterHeads,1), nodePositions(clusterHeads,2), 'r', 'filled');
title('Cluster Heads');
xlabel('X Position');
ylabel('Y Position');
legend('Nodes', 'Cluster Heads');
```

c. Assign Nodes to Clusters

```
% Calculate distances from nodes to cluster heads
distances = pdist2(nodePositions, nodePositions(clusterHeads, :));

% Allocate each node to the closest cluster head
 [~, clusterAssignments] = min(distances, [], 2);

% Plot clusters
```

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```
figure;
gscatter(nodePositions(:,1), nodePositions(:,2), clusterAssignments);
hold on;
scatter(nodePositions(clusterHeads,1), nodePositions(clusterHeads,2), 'r', 'filled');
title('Clusters');
xlabel('X Position');
ylabel('Y Position');
legend('Cluster 1', 'Cluster 2', 'Cluster 3', 'Cluster Heads');
```

3. Simulate Data Transmission and Energy Consumption

a. Define Transmission and Energy Models

```
% Transmission parameters
transmissionEnergy = 0.5;       % Energy consumed per transmission
energyDecay = 0.01;             % Energy decay factor per hop
```

b. Simulate Data Transmission

```
% Simulate transmission for each node
nodeEnergy = initialEnergy * ones(numNodes, 1);

for i = 1:numNodes
    % % Compute the energy consumed during transmission
    if nodeEnergy(i) > transmissionEnergy
        nodeEnergy(i) = nodeEnergy(i) - transmissionEnergy;
    else
        disp(['Node ', num2str(i), ' out of energy']);
    end
end

% Plot remaining energy
figure;
bar(nodeEnergy);
title('Remaining Energy of Nodes');
xlabel('Node Index'); ylabel('Remaining Energy');
```

IV. RESULTS AND DISCUSSION

This paper qualitatively compares various wireless sensor network (WSN) routing protocols to identify the most effective one for energy efficiency, a critical factor in WSNs. Specifically, it evaluates the proposed Probabilistic Routing Scheme based on Game Theory (PRGT) against the existing Cluster Chain Mobile Agent Routing (CCMAR) and Small World Wireless Sensor Network (SW-WSN) protocols.

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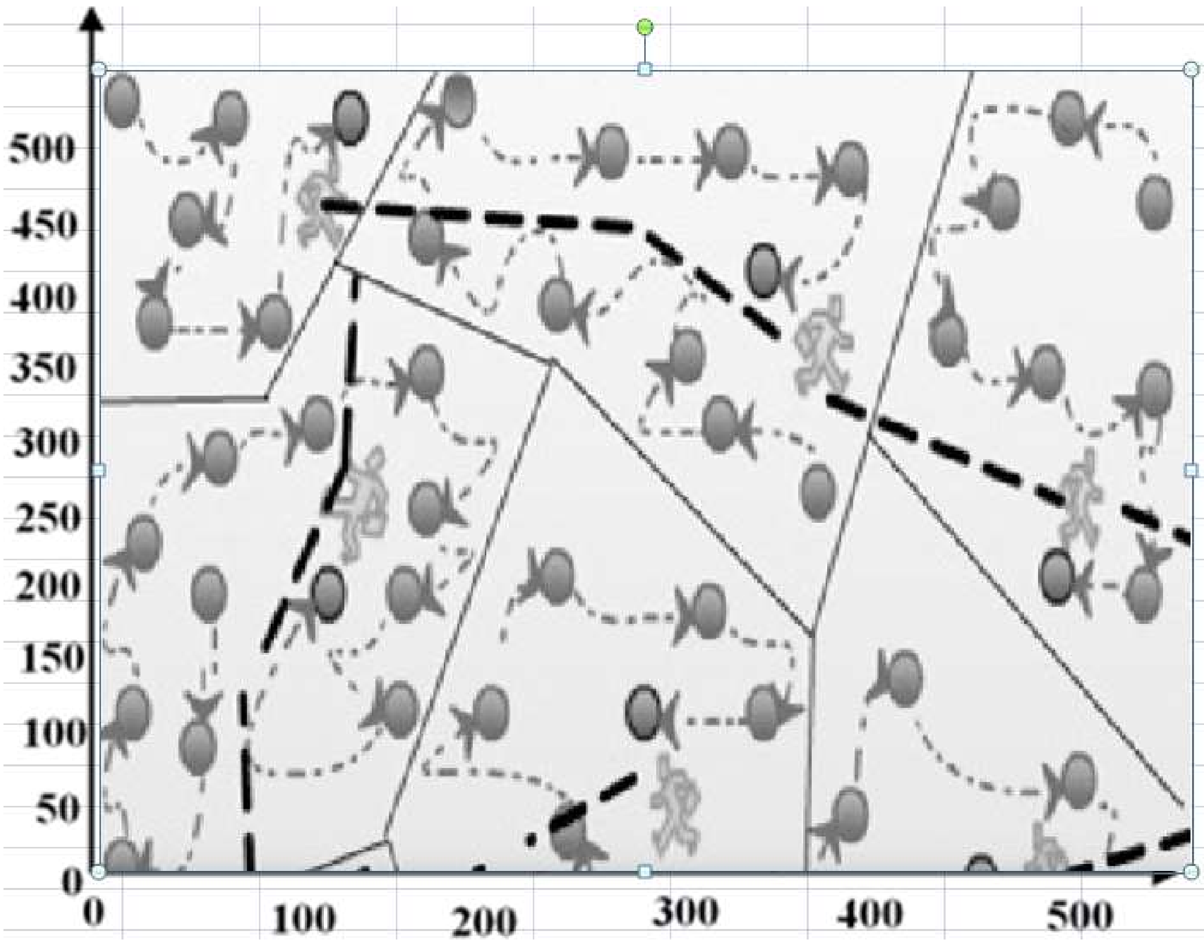

Figure.1 DT Routing.

The Figure.1 shows the transmission power level required by the DT. It is clear that the power required for the transmission is minimum in DT. This minimum transmission power also minimize the consumption of energy. From the Figure.1, it is clear that DT has the capacity to connect the network in the reverse link with each neighbor node. However DT construct an efficient routing protocol.

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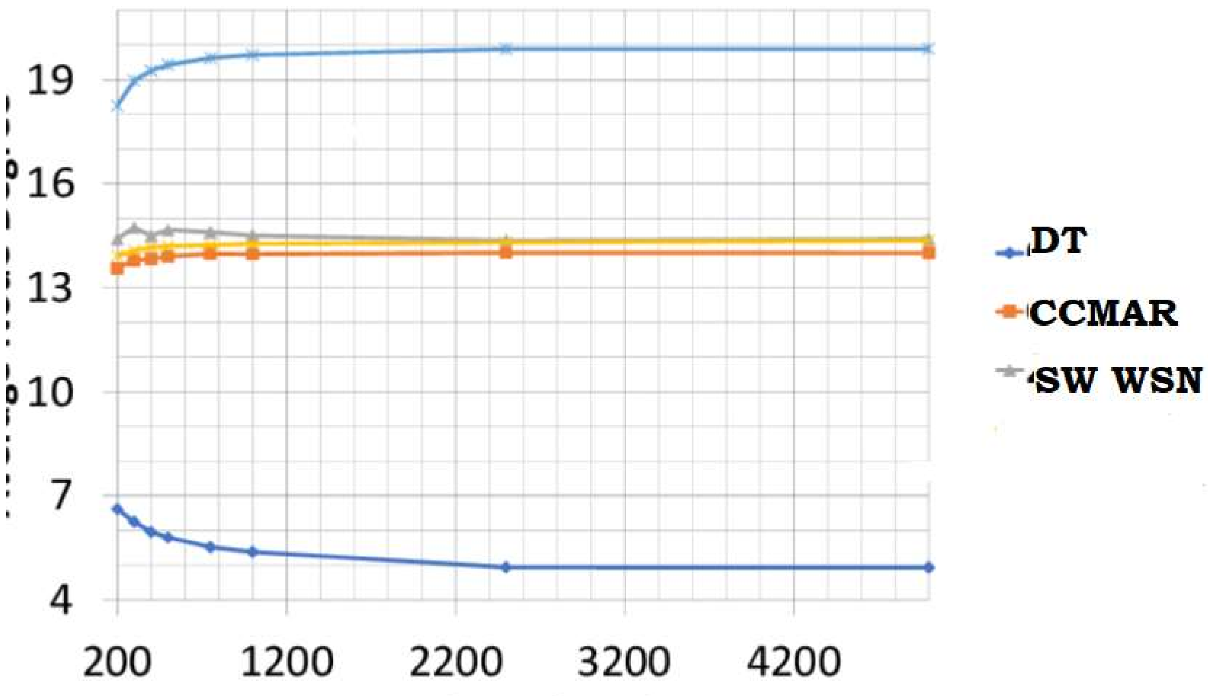
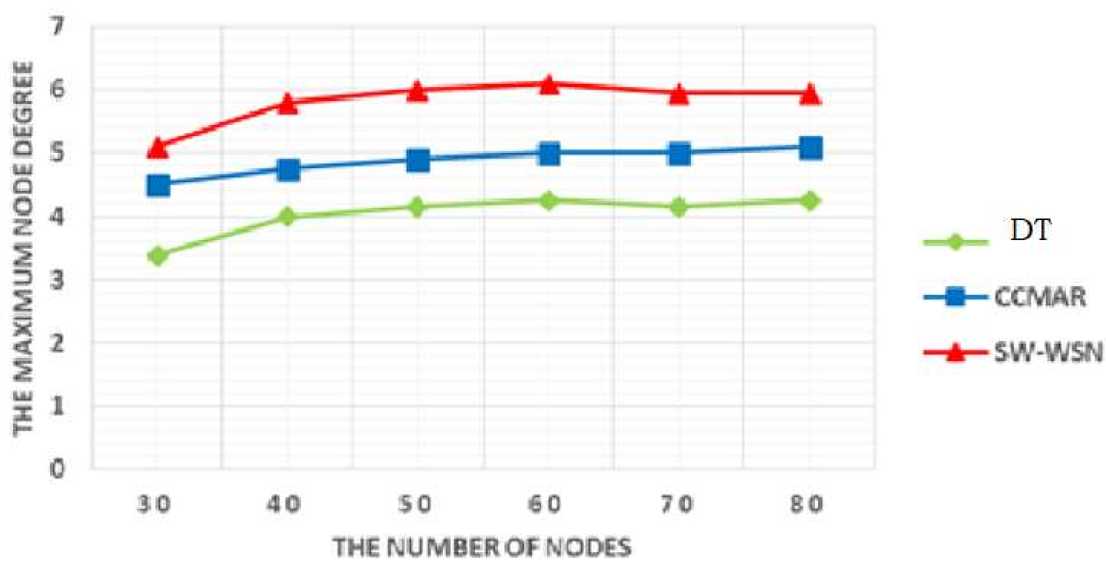


a) Average node degree.



b) Maximum node theory.
Figure.2 Average and Maximum node degree of DT, CCMAR and SW-WSN.

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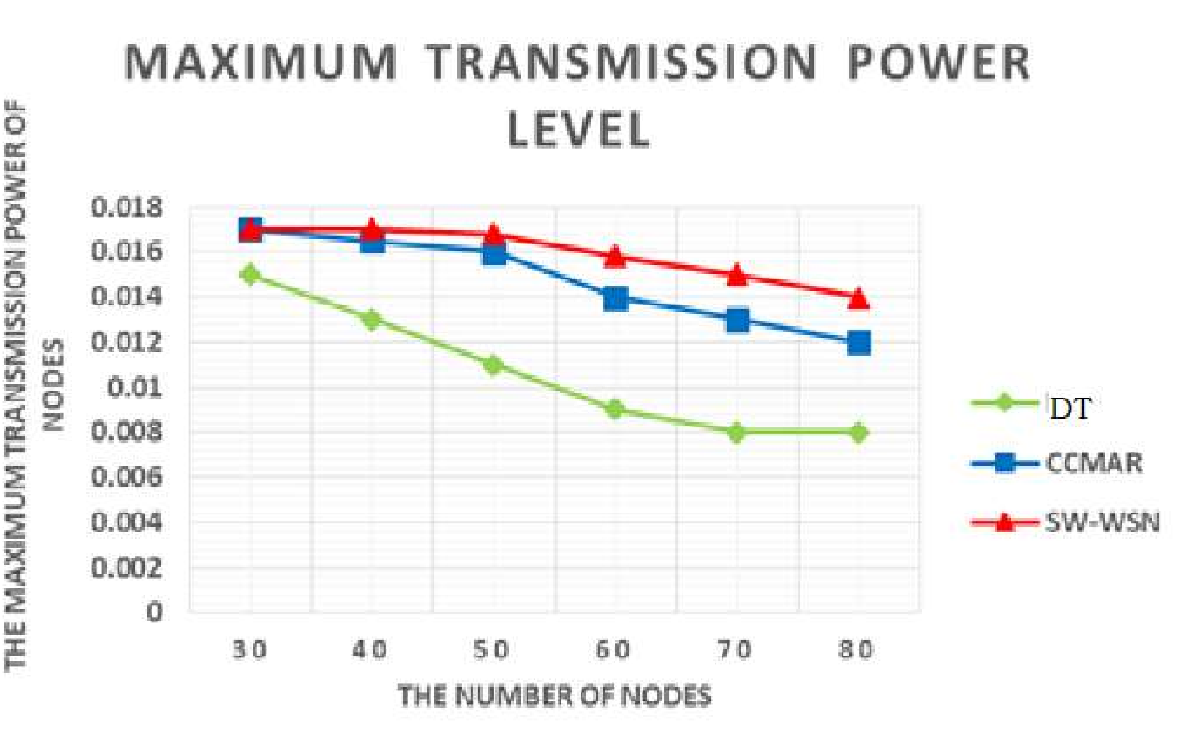
Figure 2 illustrates the mean and maximum node degrees for the DT, CCMAR, and SW-WSN networks. It is evident that the connectivity of each network is maintained by ensuring that each node has at least one connection.

Figure 2(b) shows that the DT network maintains a lower minimum degree compared to CCMAR and SW-WSN. As a result, the increase in the slope curve for DT is more gradual as the number of nodes increases.

In terms of maximum node degree, CCMAR and SW-WSN achieve values of 6.9 and 5.2, respectively, while DT has a maximum node degree of around 4.462. Additionally, the mean degree for SW-WSN and DT remains relatively constant at certain points. This means that the mean and maximum node degrees for SW-WSN are generally higher than those for DT and CCMAR.

Despite this, DT shows greater robustness in some scenarios because its node degree does not peak even when the mean degree is at its highest. This robustness is attributed to DT's lower transmission power, which helps extend the network's lifetime. Conversely, CCMAR and SW-WSN require more nodes and higher transmission power to establish their networks, making them less efficient in terms of power usage.



a) Maximum transmission power level.

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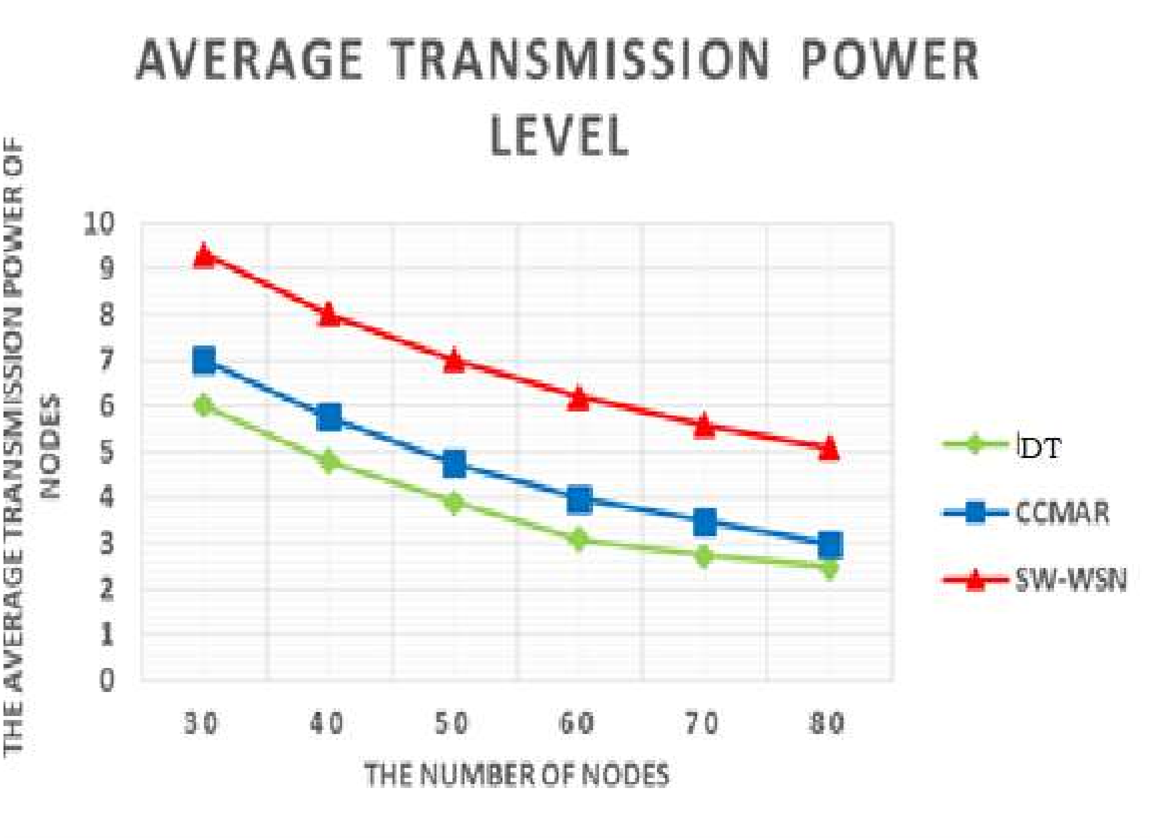

b) Average transmission power level.

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Figure 2 displays the mean, maximum, and average transmission ranges for the DT (Distributed Topology), CCMAR (Clustered Connected Multi-Hop Adaptive Routing), and SW-WSN (Sliding Window Wireless Sensor Network) protocols.

Figure 3 presents the mean, maximum, and minimum transmission power levels for these protocols. Key observations include: **DT** consistently requires lower maximum and average transmission power compared to **CCMAR** and **SW-WSN**. This indicates that DT is more energy-efficient in terms of power consumption.As the number of nodes increases, both the mean and maximum transmission power levels for DT decrease. This suggests that DT adapts well to network growth, reducing power needs as more nodes are added.The minimum transmission power level for DT does not decrease as significantly as the average or maximum levels. This is because DT maintains a certain level of power to ensure reliable connections between nodes, even when more nodes are present.

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ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
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V. CONCLUSION

In this paper, we present the decision Theory (DT) for improving routing protocols in railway network connectivity in Wireless Sensor Networks (WSNs). Our approach focuses on enhancing network performance by addressing the challenge of selfish nodes, which often hinder message forwarding. Specifically, we employ a Bargaining decision model to create incentives for nodes to participate actively in message forwarding, thereby reducing selfish behavior and promoting better network engagement. Compared to traditional routing protocols, DT offers notable improvements in various performance metrics. It reduces transmission time and enhances overall network efficiency, making it a robust and effective solution in railway connectivity for managing WSNs.

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