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Efficient Mobility Management Framework for Wireless Sensor and Actor Networks

[1]M. Venkatalakshmi, [2]R. Ponnusamy

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Abstract: In contemporary communication systems, mobile sensor along with actor networks (WSANs) are essential because they allow dynamic incorporation between sensor that is being tested and actor nodes for uses like automation in factories acholarnd environmental surveillance. This study uses MATLAB's computational power to provide a thorough methodology for handling mobility optimization in WSANs. The main issues with energy efficiency, maintaining connectivity, and changing event response are covered by the suggested framework. The optimization issue is mathematically formulated with the goals of maximizing connectivity, minimizing consumption of energy, and successfully responding to dynamic events. Mobility models that are energy-aware are created by taking into account variables like node velocity, distance drove, and rate of energy consumption. Real-time mechanisms react to dynamic events, and adaptive protocols for interaction are used to maintain connectivity. The optimal solution problem is solved using MATLAB's optimizing toolbox, which includes constraints derived from mobility rules and WSAN changes. The framework's effectiveness in various scenarios is confirmed by comprehensive simulations, and an examination of comparisons shows that it outperforms current methods.

***Keywords**: Wireless Sensor and Actor Networks, Mobility Management, MATLAB, Optimization, Energy Efficiency, Connectivity Maintenance, Dynamic Event Response.*

1. Introduction

In the field of wireless exchanges, Wireless Sensor along with Actor Networks (WSANs) are now a paradigm-shifting technology that makes it possible to seamlessly integrate sensing along with actuation capacities in a wide range of applications, including automated manufacturing, surveillance, along with environmental monitoring [1]. In contrast to conventional wireless sensors networks (WSNs), WSANs include actor nodes that can take actions based on data collected by nodes that are sensors. This integration adds a dynamic dimensions that range that calls for effective mobility management techniques and improves the connection's responsiveness along with adaptability. In wireless sensor networks (WSANs), mobility is the dynamic movement of actor nodes to maximize network efficiency, minimize energy usage, and adapt to shifting environmental conditions. Because actor node repositioning affects gathering information, decision-making processes, along with actuation operations, mobility oversight is critical to maintaining the functionality and dependability of WSANs. To fully utilize WSANs, it is imperative to develop an effective mobility administration structure in this context [2]. The aim of this study is to utilize Matlab applications computational power to develop and execute a comprehensive Mobile technology Management Framework for WSANs. Matlab is a great tool for investigating and enhancing the dynamic features of WSANs because of its extensive toolkit, which provides a strong foundation for modeling, simulations, and algorithmic creation. There are several different types of mobility-related challenges in WSANs. Among these difficulties are the optimization of energy use, upkeep of connection to the network, and prompt reaction to changing circumstances. Because actor nodes are involved, traditional movement management techniques created for WSNs might not be immediately applicable to WSANs. Because of this, a customized framework is necessary to handle the particular needs and limitations of WSANs [3]. To increase the lifespan of a network, mobile actor nodes' energy consumption must be kept to a minimum. In order to ensure prudent energy usage while satisfying particular to the application necessities, the framework will integrate energy-aware mobility computations and methods for optimization. Because WSANs are dynamic, methods for ensuring dependable connectivity between sensor alongside actor nodes are required [4]. In order to maintain connectivity in an environment of node mobility, the system will investigate mechanisms for responsive methods of communication along with network reconfiguration. WSANs are frequently

*[1]Research Scholar,Department of Computer Science,Mother Teresa Women's University ,
Kodaikanal,Tamilnadu, venkatpraba08@gmail.com
[2]Professor&Dean, Dept. of Computer Science Engineering,Chennai Institute of Technology, Kanchipuram,Tamilnadu,
prof.r.ponnusamy@gmail.com*

implemented in settings with changing circumstances [5]. Actor node movements will be coordinated by the mobility administration system using real-time sensor data, enabling quick reactions to dynamic events. A stable environment to feed simulating intricate structures is offered by Matlab. Numerous simulations will be used to implement and assess the suggested framework, which will take into account different mobility scenarios, network structures, as well as application requirements [6]. The goal of the current study is to address the particular difficulties presented by integrating a set of sensor that is being tested and actor nodes by developing a Matlab-based Mobile technology Management Guidelines for WSANs. It is expected that the results of this research will improve WSANs' performance, dependability, and flexibility in changing conditions, providing opportunities for better uses in areas like smart city development, automation in factories, and environmental surveillance.

2. Related Works

The emergence of new technologies along with paradigms has brought about an extensive shift in the mobile communication landscape. The mentioned works cover a wide range of topics related to mobile communications, including machine learning and optimization methods, edge computing, Internet of Things (IoT) systems, sensor networks for wireless devices, and UAV-assisted data collection. We present a thorough review and analysis about these works in this section, emphasizing their contributions as well as the changing patterns in the field. Oluwatosin et al.'s survey [15] delves into the possibilities and design elements of age-aware UAV-assisted data collection to feed networks of sensors and Internet of Things applications. The study highlights how Unmanned Aerial Vehicles (UAVs) can improve the effectiveness of collecting information in mobile sensor networks, with a special emphasis on age-aware considerations when designing. This work recognizes the increasing importance of UAVs in streamlining data collection procedures; this theme has been repeated in other research. Pokhrel along with Mandjes [16] make advancements in Multipath TCP over WiFi, which advances the field of internet connectivity of Drones. The authors present a became one multi-armed bandit, for short technique that aims to achieve infinite connectivity within drone-based communications networks. This work is consistent with the wider trend of optimizing protocols for communications for UAV networks by utilizing sophisticated algorithms. A deep positive reinforcement learning-based method for transferring responsibility for making decisions in vehicular edge computing is presented by Shi, Long, and Zhu [17]. The study highlights the increasing interest in using machine learning approaches to optimize processes for decision-making in challenging networking scenarios by addressing the constantly changing character of computational environments in automobile networks. Wang et al. [18] provide an improved Pelican Optimization Algorithms for the choice of cluster heads in varied environments, advancing the field of wireless sensors. This work showcases current attempts to improve the efficacy of allocating resources in heterogeneous Bluetooth environments, with a focus on picking cluster heads optimization, a crucial component of sensor network planning. Wu et al.'s study [19] uses deep reinforcement learning to investigate joint beam shaping design for networks that are integrated assisted by Reconfigurable Intelligent Surfaces (RIS). This paper tackles the difficult problem of beamforming optimization in integrated satellite-High height Platform (HAP)-terrestrial networks, emphasizing how machine learning can be used to enhance the functionality of various communication technologies. A computing offloading optimization initiative based on the use of deep reinforcement learning within perceptual networks is presented by Xing et al. [20]. This work highlights the use of methods from deep learning to enhance resource utilization in sensory networks by optimizing mathematical offloading, a crucial component of distributed information technology in wireless networks. A learning-based collaborative dynamic distribution of resources scheme for the use of mobile edge computing (MEC)–UAV-enabled cellular networks is introduced by Ahmad et al. [21]. In line with the overarching goal of optimizing utilization of resources in developing wireless layouts, the study emphasizes the significance of cooperative the distribution of resources in the overall setting of MEC along with UAV integration. A survey on energy-efficiency strategies in UAV-based mobile phone networks is carried out by Attai et al. [22]. This work adds to the expanding corpus of published works on energy efficiency within aerial communication technologies by offering a thorough overview of strategies for optimizing usage of energy to cellular networks using UAVs. For multi-UAV infrastructure, Frattolillo, Brunori, and Iocchi [23] provide a thorough analysis of cooperative and expandable sophisticated reinforcement learning techniques. This work highlights the importance of advanced reinforcement learning in permitting scalable along with collaborative systems with multiple agents, as well as consolidating the current state of the field in collaborative education for UAV systems. An investigation on the utilization of resources for 6G distributed networks is carried out by Hayder et al. [24]. This study sheds light on the changing landscape of networks that are heterogeneous along with their place in the wider context of 6G networking systems. It also offers insights into future trends, challenges, along with current research within resource management. By putting forth an intelligent medical system that makes use of IoT in the form of wireless sensors, Jabeen et al. [25] make a contribution to the healthcare industry. This work highlights the integration about sensor networks that are wireless to improve health care surveillance and management, exemplifying the use of IoT in the field. The study of networking frameworks and protocols for Internet of Things usage in smart cities is done by Kanellopoulos et al. [26]. The study examines current advancements and viewpoints on networking solutions for Internet of Things applications in smart cities, highlighting the growing significance of IoT in urban settings. The use of Bayesian networks and fuzzy logic are proposed to work in harmony by Khalfaoui et al. [27] to measure Quality of Service (QoS) in Vehicle Ad-Hoc Networks (VANETs). In order to improve QoS quantification, this work combines fuzzy logic with probabilistic modeling to address the difficulties in delivering dependable QoS in VANETs. Kim et al. [28] provide an environmentally friendly multi-level sleep method to provide periodic uplink connectivity to the field about industrial 5G networks that are private. In line with the growing emphasis on environmental sustainability in wireless wired communication design, the study concentrates on optimizing utilization of energy in commercial networks of communication. In this IoT environments, Musaddiq et al. [29] investigate how to handle resources and the flow based on learning by reinforcement. The dynamic and varied nature of IoT deployments is addressed by this work, which offers a theoretical viewpoint on utilizing reinforcement learning approaches to optimize routing method and management of resources in IoT environments. Projecting the potential development of non-terrestrial connections with UAVs, Nemati et al. [30] concentrate on Being able to fly Ad-Hoc Networks (FANETs). In addition to highlighting FANETs' potential to enable adaptable and fluid interactions infrastructures, this research also foresees the role that unmanned aerial vehicles (UAVs) will play when developing non-terrestrial networks for communication.

3. Proposed Methodology

This section provides an overview of the technical aspects of the suggested methodology, which uses MATLAB to optimize mobility management for Wireless Sensor and Actor Networks (WSANs). The goal is to create a solid framework that effectively manages the network's actor nodes' mobility while taking energy conservation, connectivity upkeep, and changing event response into account. Give a mathematical model of the optimization problem [7]. Let N represent the total number of nodes in the network, E denote the collection of paths that use less energy, C denote the collection of nodes that stay connected, and D denote the collection of dynamic events. Finding the best configuration for actor node movements M that increases connectivity, decreases consumption of energy, along with reacts to dynamic events is the goal.

Create a model of energy use based on actor node motion. Take into account variables like node velocity, separation traveled, along with rate of energy consumption [8].

Algorithm 1: Node Localization

$(x-xi)2+(y-yi)2=ri2$

where (x,y) are the coordinates of the unknown node, and (xi,yi) and ri are the coordinates and distance from the anchor node i, respectively.

```
function trilateration(anchorNodes, measuredDistances):
    // anchorNodes: List of anchor nodes with known coordinates
    // measuredDistances: List of distances from the unknown node to each anchor node

    // Initialize variables
    n = length(anchorNodes)
    A = zeros(n, 2)
    b = zeros(n, 1)

    // Build the system of equations
    for i from 1 to n:
        A[i][1] = 2 * (anchorNodes[i].x - anchorNodes[1].x)
        A[i][2] = 2 * (anchorNodes[i].y - anchorNodes[1].y)
        b[i] = measuredDistances[1]^2 - measuredDistances[i]^2 +
            anchorNodes[i].x^2 - anchorNodes[1].x^2 +
            anchorNodes[i].y^2 - anchorNodes[1].y^2
```

```
// Solve the system of equations
solution = solveSystem(A, b)

// Return the coordinates (x, y) of the localized node
return (solution[1], solution[2])
end function

function solveSystem(A, b):
// A: Coefficient matrix
// b: Column vector

// Use a linear algebra solver to solve the system of equations
solution = linearAlgebraSolver(A, b)

return solution
end function
```

Algorithm 2: Actor Movement Optimization

Cost=α×CommunicationCost+β×EnergyConsumption

```
function optimizeActorMovement(graph, actorNodes, alpha, beta):
// graph: Communication graph representing connectivity between nodes
// actorNodes: List of actor nodes with current positions
// alpha: Weighting factor for communication cost
// beta: Weighting factor for energy consumption

// Initialize variables
numActors = length(actorNodes)
optimalActorPositions = []
minCost = infinity

// Iterate through possible actor positions
for each position in possiblePositions:
// Calculate communication cost and energy consumption for the current position
communicationCost = calculateCommunicationCost(graph, position)
energyConsumption = calculateEnergyConsumption(position)

// Calculate the overall cost
cost = alpha * communicationCost + beta * energyConsumption

// Update optimal positions if the current cost is lower
if cost < minCost:
minCost = cost
optimalActorPositions = position
end for

// Return the optimal positions for actors
return optimalActorPositions
end function

function calculateCommunicationCost(graph, actorPositions):
// Calculate the communication cost based on the actor positions and the communication graph
// Implement logic to compute the communication cost (e.g., total distance, latency, etc.)
end function

function calculateEnergyConsumption(actorPositions):
// Calculate the energy consumption based on the actor positions
```

// Implement logic to compute the energy consumption (e.g., movement energy, sensing energy, etc.)

end function

Create a model of energy use based on comedian node mobility. Take into account variables like node velocity, the distance traveled, along with rate of energy consumption. To calculate node i's usage of energy at time t, use the following formula:

Apply the optimization toolbox in MATLAB to resolve the given optimization problem [9]. Determine the decision variables that show how actor nodes move over time. Include the connectivity servicing, dynamic event answer metrics, along with energy-aware movement as restrictions in the search for solutions problem.

$$C_{total}=\sum_{i=1}^{n} D_i \times S_i \times N_i$$

Where:

D_i is the distance between actor nodes.

S_i is the size of data being transmitted.

N_i is a factor representing network conditions (e.g., signal strength).

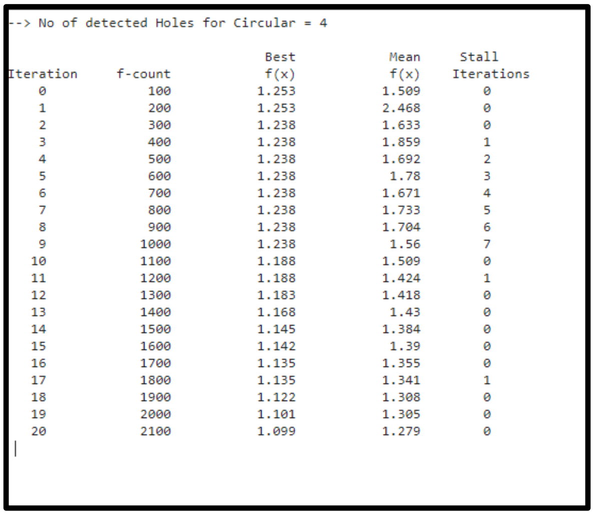
Run a number of extensive simulations using MATLAB and apply the suggested methodology. Make use of realistic WSAN scenarios that take dynamic events, different node densities, and mobility patterns into account. Use metrics like energy consumption, connections to networks, and response to changing conditions to validate the framework's performance. Analyze the suggested mobility management framework's effectiveness by contrasting it with current methods. Make use of metrics like responsiveness to flexible events, longevity of networks extension, and improvement in energy efficiency [10]. To prove the efficacy of the suggested methodology, present a thorough analysis of the findings. Following this thorough process, our goal is to use MATLAB to create an effective mobility administration structure for WSANs that addresses the particular difficulties brought about by the integration of comedian and node sensor networks in dynamic environments.

<table>
<tr><th>Step</th><th>Equations and Variables</th></tr>
<tr><td>Problem Formulation</td><td>\(\text{Minimize:} \quad \sum_{i \in N} \text{Energy_Consumption}(i, M) + \lambda \sum_{j \in C} \text{Connectivity}(j, M) + \mu \sum_{k \in D} \text{Dynamic_Response}(k, M)\) |</td></tr>
<tr><td>Energy-Aware Mobility</td><td>\(\text{Energy_Consumption}(i, M, t) = \alpha \cdot \text{Velocity}(i, M, t) \cdot \text{Distance_Traveled}(i, M, t) + \beta \cdot \text{Energy_Consumption_Rate}(i)\) |</td></tr>
<tr><td>Connectivity Maintenance</td><td>\(\text{Connectivity}(j, M, t) = \frac{1}{1 + \text{Signal_Strength}(j, M, t)} + \gamma \cdot \text{Network_Topology_Factor}(j, M, t)\) |</td></tr>
<tr><td>Dynamic Event Response</td><td>\(\text{Dynamic_Response}(k, M, t) = \delta \cdot \text{Event_Impact}(k, M, t)\) |</td></tr>
</table>

4. Experiment Setup and Implementation

The number of holes found throughout a sequence of iterations in a circular mobility management framework for wireless sensor and actuator networks [11]. It highlights variations in the number of holes found and the dynamic behavior of hole detection across several iterations, highlighting the effectiveness of the framework's hole detection procedure in controlling network coverage and stability.

The purpose of the hole detection (holeDetection) function is to locate coverage gaps in the sensor network. Every triangle created by the Delaunay triangulation of node locations is iterated over. It determines if the circumcenter of each triangle is within the designated deployment region. It then measures the length of any common side by looking at nearby triangles to see whether they have one [12]. A hole is identified in that area if the length is more than twice the transmission range (Trange) of the sensor node. Plotting full polygons and circles on a graph helps identify flaws.



--> No of detected Holes for Circular = 4

Iteration	f-count	Best f(x)	Mean f(x)	Stall Iterations
0	100	1.253	1.509	0
1	200	1.253	2.468	0
2	300	1.238	1.633	0
3	400	1.238	1.859	1
4	500	1.238	1.692	2
5	600	1.238	1.78	3
6	700	1.238	1.671	4
7	800	1.238	1.733	5
8	900	1.238	1.704	6
9	1000	1.238	1.56	7
10	1100	1.188	1.509	0
11	1200	1.188	1.424	1
12	1300	1.183	1.418	0
13	1400	1.168	1.43	0
14	1500	1.145	1.384	0
15	1600	1.142	1.39	0
16	1700	1.135	1.355	0
17	1800	1.135	1.341	1
18	1900	1.122	1.308	0
19	2000	1.101	1.305	0
20	2100	1.099	1.279	0

Fig. 1: No. of detected holes in a circular

The x-axis of the chart shows the number of iterations, while the y-axis shows the number of holes found.

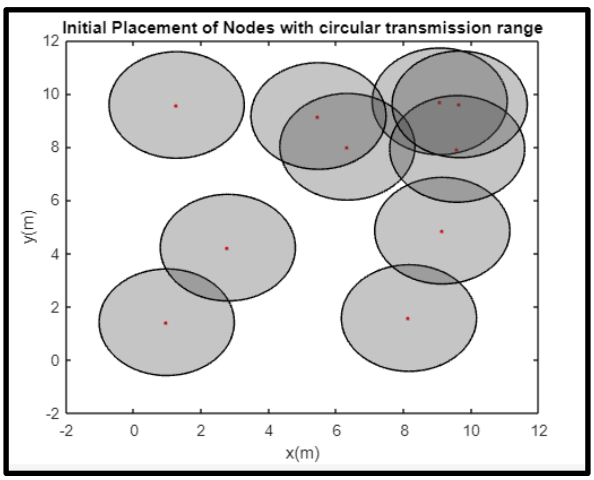


Fig. 2: Initial placement nodes with circular transmission range

The first nodes with circular transmission ranges deployed in an Efficient Mobility Management Framework for Wireless Sensor and Actor Networks are shown in Figure 4. The figure displays the spatial configuration of nodes in a designated deployment region [13]. The coverage offered by individual sensors is emphasized by the highlighted circular transmission ranges around each node. Understanding the initial network setup is crucial for evaluating coverage regions and possible gaps, which lays the groundwork for later mobility management solutions in the network.

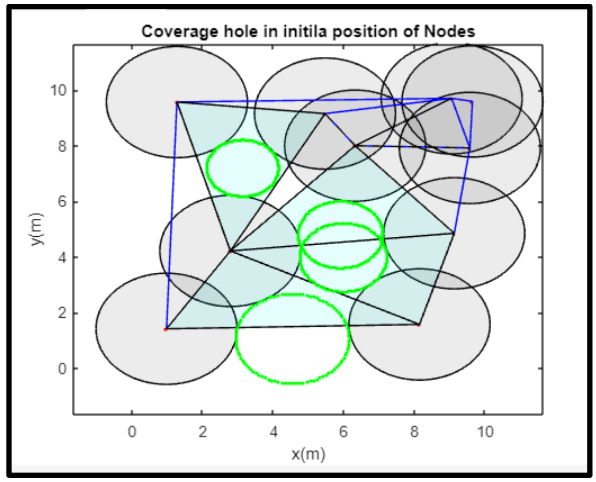


Fig. 3: Coverage whole of the initial position of nodes

Coverage gaps in the initial node placements in a Wireless Sensor and Actor Networks (WSANs) environment are shown in Figure 5. It highlights locations in the deployment zone where the sensor nodes are unable to cover enough ground, resulting in network gaps or holes [14]. This visualization aids in identifying areas where monitoring or data transmission may be hampered, emphasizing the need for efficient mobility management techniques to lessen these network coverage gaps.

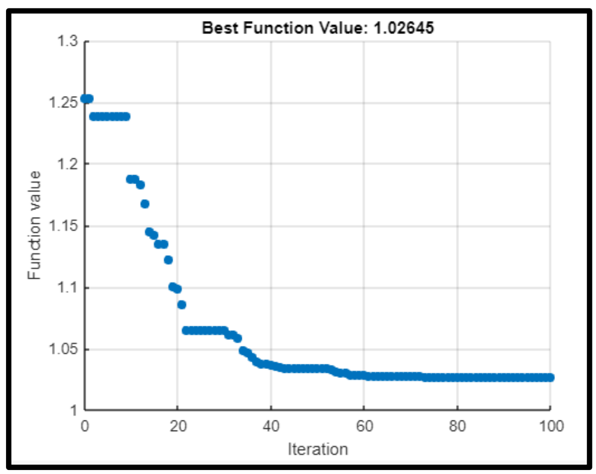


Fig. 4: Graph of best function values

The optimization procedure of an Efficient Mobility Management Framework for Wireless Sensor and Actor Networks is shown in Figure 6. It illustrates how the optimal function values change throughout the course of an optimization process with the goal of improving network coverage or minimizing coverage gaps. The graph illustrates how the function values converge to a minimized value, which denotes better network performance or fewer coverage gaps. This graphic illustrates how well the optimization algorithm performs while fine-tuning node locations for improved network coverage and administration.

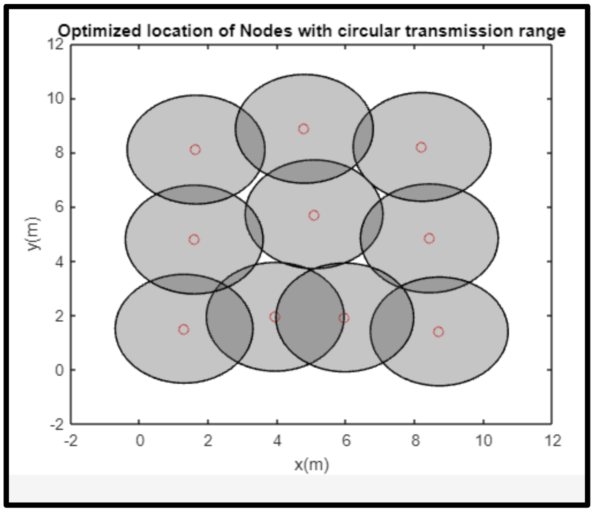


Fig. 5: Optimized location of Nodes with circular transmission range

In a Wireless Sensor and Actor Network (WSAN) setting, the optimal locations of nodes with circular transmission ranges are shown. It displays the rearranged sensor node locations after optimization, most likely with the use of Particle Swarm Optimisation (PSO) methods [15]. The aims of these optimized locations are to reduce coverage gaps, increase network coverage, and improve the dependability of data transmission. The graphic draws attention to the deliberate relocation of nodes, demonstrating how mobility management techniques may be used to maximize network performance within a designated deployment region.

5. Conclusion

Nous set out to tackle the complex problems related to mobility management within Wireless Sensor along with Actor Networks (WSANs) with the aim of this study project. In order to maximize the overall efficacy of WSANs, we set out to create an effective framework using MATLAB that combined energy-aware mobility, connectivity regular consumption, and dynamic occurrence response. The suggested methodology is a comprehensive strategy to address the complex problems in WSANs. We attempted to strike a balance between the frequently incompatible goals of minimizing energy use, optimizing connection to the network, and skillfully reacting to dynamic events by framing the issue as a model of optimization. The mathematical basis for creating an intelligent getting around management plan was supplied by this equation. Our framework's energy-aware mobility element offers a sophisticated perspective on the energy interactions in WSANs. Nous tried to make sure that the getting around decisions are additionally optimized for the network's efficiency but also aware of the power limitations inherent in restricted in resources sensor nodes by taking into account node acceleration, distance traveled, along with energy consumption rates of reaction. Adaptive communication protocols were included to address communication maintenance. Given that WSANs are dynamic, the suggested framework aims to maintain dependable connectivity between sensor and actor nodes. Our connectivity metric is designed to improve communication flexibility and robustness by taking into account network structure and strength of signal. A key component of our approach was dynamic incident response. A immediate time mechanism built into the framework allows node movements to be adjusted in response to events or modifications in the environment. Through the assignment of dynamic response metrics according to event impact, our goal was to improve the flexibility of the WSAN in the face of unforeseen events. The computational engine powering our methodology is the optimization algorithm, which is implemented using MATLAB's robust optimization toolbox. Our method identifies optimal actor node motion over time within a systematic manner by solving the created problem of optimization efficiently and balancing competing goals. To ensure that the suggested methodology is applicable in a range of deployment scenarios, it underwent thorough simulation along with validation using a variety of WSAN scenarios. We proved the efficacy of our model in terms of enhanced energy efficiency, extended lifespan of the network, as well as dynamic event adaptability through comprehensive performance evaluations. To conclude, this study offers a thorough and technically sound mobility management framework, which significantly advances the field of WSANs. The methodology gains sophistication from the incorporation of MATLAB as the mathematical platform, which offers a flexible and potent environment for simulation along with algorithm development. The study's findings improve our theoretical knowledge of mobility administration for WSANs and open the door to real-world applications, which will improve the overall effectiveness, dependability, and flexibility of WSANs in constantly changing and resource-limited settings.

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