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Optimization of Fuzzy Logic-Based Genetic Algorithm Techniques in Wireless Sensor Networks Protocols

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Abstract: The operational timeline of a Wireless Sensor Network (WSN) spans from the initiation of sensing activities until a predetermined proportion of nodes deplete their power reserves, with the "critical node" being the specific device undergoing power depletion. Optimizing WSN longevity, particularly of these critical nodes, is pivotal for overall network sustainability. The network involves relay nodes communicating with a central hub through intermediary nodes, extending longevity, enhancing accessibility, and efficiently managing traffic distribution in alignment with sensor network design principles.

To extend network operational lifespan, we propose a strategy utilizing a Genetic Algorithm embedded with Fuzzy Logic (FLbGA) to orchestrate relay nodes' data collection schedules. Relay nodes, acting as hand-off hubs, aggregate information within their groups or neighboring transfer hubs. This data is transmitted to the base station directly or through an interconnected sequence of intermediate relay nodes. The strategic use of FLbGA optimizes data collection, boosting network durability and performance.

In each designated cluster, relay nodes receive data from corresponding sensor nodes, where transmitted information may exhibit constancy or variability. Assuming post-deployment spatial node configurations, parameters like population size, cross-over frequency, mutation frequency, etc., are integrated into FLbGA's design for an optimal solution. This parameter augmentation enhances the system's efficiency and adaptability.

Keywords: *Wireless Sensor Network, critical node, relay nodes, Genetic Algorithm, Fuzzy Logic.*

1. Introduction

Recent attention in academic circles has been heavily directed towards Wireless Sensor Networks (WSNs), prompting a need for comprehensive studies to establish a solid foundation in this domain. WSNs, comprising a collection of sensor devices forming an ad-hoc network, aim to achieve objectives such as environmental monitoring, decision-making, and transmitting pertinent information to legitimate endpoints. To optimize operational efficiency, reduce communication overheads, and alleviate interference among Sensor Nodes (SNs), sensor networks employ clustering algorithms [1]. As proposed by [2], the fundamental justification for utilizing clustering routing pertains to the imperative need for data reduction within the network architecture. This is achieved through the information pooling process of Cluster Heads (CHs), alleviating the strain on SNs' power supply by minimizing energy requirements for communication. Furthermore, the implementation of clusters contributes to increased network uptime by optimizing load balancing, ensuring even distribution of responsibilities among CHs and thereby prolonging the overall network lifespan. This strategic division of responsibilities aims to extend the sustainability of the network architecture [2].

In the realm of optimization methodologies, this research delves into Wireless Sensor Network (WSN) clustering protocols. The investigation involves a comprehensive review and analysis of protocols, examining the methodologies and attributes of various algorithms with a particular emphasis on recent advancements in optimized clustering solutions. The study evaluates how these protocols perform across different network topologies, considering both the standard boundaries of group conventions and the improvement process boundaries specific to each case. To ensure a precise evaluation and a comprehensive understanding of clustering procedures, the analysis incorporates optimization parameters. These parameters are meticulously selected after considering a variety of optimization strategies, contributing to a nuanced and thorough assessment of the methods employed in WSN clustering protocols. Our contributions encompass innovative perspectives and methodologies in optimization for clustering protocols, spanning meta-heuristic, fuzzy, and hybrid strategies.

- Introduction of a novel viewpoint and approach to optimization methods in clustering protocols.

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- Proposal of a fresh categorization approach grounded in optimization algorithms.

- Pioneering the evaluation of Wireless Sensor Network (WSN) protocols by optimizing clustering parameters.

2. Literature Reviews

Introduction to Sensor Network Optimization: Explore clustering approaches and optimization strategies to enhance sensor network performance in diverse conditions. Aimed at assisting academics in understanding clustering-based optimization strategies, categorizing them based on optimization methods, and addressing fundamental constraints of existing clustering methods.

Evaluation of Routing Algorithms: First attempt to assess routing algorithms employing swarm intelligence, considering potential applications and simulation environments. Limited focus on swarm-based protocols, particularly excluding protocols beyond swarm intelligence.

Categorization of Group-Based Steering Procedures: In [3], authors categorized group-based steering procedures for homogeneous sensor networks (SNs) based on goals and clustering approaches. Factors considered include Cluster Head (CH) determination, information total, group development, and data transmission.

Comprehensive Review of Clustering Methods: Systematic categorization of clustering methods for homogeneous networks from 2011 onward. Inclusion of relevant prior research to offer a comprehensive perspective on clustering techniques.

Assessment Schemes for CH Selection Techniques: Application of supported, multi-dimensional, and autonomously organized evaluation frameworks [4] for classifying CH selection methods. Enhances understanding of diverse methods for selecting Cluster Heads in sensor networks.

This research systematically evaluates 16 prominent clustering algorithms in Wireless Sensor Networks (WSNs), categorizing them into information transmission and group development steering approaches. The study deliberately excludes novel methods, such as fuzzy and transformative-based strategies, focusing on conventional clustering protocols [5]. Addressing the advantages and drawbacks of hub bunching procedures in WSNs, the paper introduces a taxonomy of fuzzy and hybrid fuzzy-based clustering strategies [6]. The exploration systematically categorizes cluster-based routing strategies into block, chain, and grid-based classifications, evaluating their scalability, cluster stability, delivery latency, and energy efficiency [7]. An additional scrutiny of clustering techniques reveals strengths and weaknesses, distinguishing between block-based, matrix-based, and chain-based grouping strategies. Existing approaches are assessed based on parameters such as delivery latency, energy consciousness, load balancing, cluster stability, and algorithmic efficacy [8]. The study also considers homogeneous and heterogeneous WSNs, classifying various clustering procedures based on standards such as the number of clusters, CHs, clustering objects, and procedural complexity, accounting for network hub and resource constraints [9]. Unequal clustering methods are explored in terms of goals and characteristics, categorizing them into probabilistic, preset, and deterministic groups, with energy consumption and lifetime calculations conducted through simulations [10]. The clustering approaches are further classified into classical, fuzzy-based, meta-heuristic, and hybrid meta-heuristic based on general order boundaries and measures, considering both clustering and methodology parameters [11].

Multiple computational intelligence (CI) approaches, encompassing swarm intelligence, fuzzy logic, neural networks, genetic algorithms, and reinforcement learning, were employed to classify various computations. The study emphasized scalability, data transmission rate, and data accumulation in these CI applications [12]. The utilization of these techniques notably improved both the network's lifespan and service quality. Additionally, hybrid model combinations were found to enhance network interference [13].

3. Implementation of Routing for FLbGA

Exploring our high-level relay node network intricacies, it operates on a two-tiered architecture employing an FLbGA-based routing algorithm. This proposed algorithm aims to optimize the network's longevity by determining an efficient data collection strategy for a dual-layered Wireless Sensor Network (WSN).

In a dual-layered remote sensing structure with n transfer hubs (1, 2, 3, ..., n) and a singular base station (n+1), each transfer hub aligns with a group head. Each sensor hub is an integral part of precisely one cluster, denoted by D representing the collection of all sensor hubs forming m clusters.

In the paradigm of wireless sensor networks (WSNs), the sensor nodes within a specific cluster autonomously transmit their collected data to the designated cluster-centric hand-off hub. In turn, the transfer hubs, organized in distinct clusters, relay their respective data sets to the central base station. A critical condition for the data transfer between a source transfer hub, denoted as hub I, and a recipient hub, denoted as hub j, necessitates that hub j lies within the transmission range of hub I and is closer to the base station than hub I. Remarkably, data transmission from the base station to any of the transfer hubs is precluded, as the base station exclusively functions as a receiver in this communication architecture.

Assumptions underpinning this model include the equitable distribution of energy access among all relay nodes from the inception of the network operation. In each operational round, every relay node consistently receives a uniform quantity of bits, albeit this quantity may vary among distinct nodes. Notably, the relay node network in this framework adheres to the "non-flow-splitting" model. In this model, each relay node's outgoing data exhibits an exclusive trajectory, directed towards a singular destination within the architecture—be it another relay node or the base station itself. A salient constraint imposed by this model is the prohibition of concurrently creating multiple data flows from a single relay node to diverse destinations [14].

In this context, the calculation of the routing schedule is attributed to the base station or another power-independent location. It is imperative that all deployed nodes remain stationary, with relay nodes being either predetermined during their initial configuration or capable of reporting their current position. In this context, a fundamental premise revolves around the generation of standardized data by individual sensor hubs and their subsequent arrangement into clusters. Each transition hub is equipped with an equal initial energy provision, aligning with the previously expounded framework. As elucidated earlier, the routing schedule is centrally orchestrated, strategically considering the spatial deployment of transfer hubs and their anticipated data throughput. This orchestrated approach ensures a coherent and efficient data transfer process within the network infrastructure, maintaining the scientific rigor integral to the scenario. It is assumed that nodes may be preloaded with the computed routing schedule prior to deployment, or alternatively, the schedule can be simultaneously disseminated to all nodes. In the latter scenario, it is pertinent to highlight that the quantum of data transmitted for the establishment of the initial configuration is exceptionally minimal, thereby exerting a negligible impact on the overall network lifespan. Further exploration into the intricacies of crafting an evolutionary algorithm specifically tailored for energy-efficient routing is imperative for comprehensive understanding, [15].

Generating a Destination Node at Random

The random destination generation for the initial population in a network must adhere to specified flow requirements.

In a designated cluster, sensor nodes furnish information to their respective hand-off hubs. The data transfer hub has the capability to acquire information from other hand-off hubs within the network. The transmission of data unfolds from node i to another node f, where f is positioned within the transmission range of i and is in closer proximity to the base station. It is essential to note that the initiation of data transmission does not stem from the base station towards any relay nodes; instead, solely the reception process takes place at the base station [16].

Initialize an integer array of size n with zero values, representing the absence of connections in the network of size n+1. Designate node 1 as the origin and randomly select a destination node f from the range 1 to n+1, ensuring adherence to flow constraint 2. Update the value in column l from 0 to f, designating node f as the terminal destination for node 1. Subsequently, randomly select an integer k, denoting the objective hub for f, from the range 1 to n+1 while satisfying the aforementioned flow prerequisite. Notably, f serves as the source hub, excluding the base station.

If k is not the base station, iterate the process until the base station is identified as the ultimate hop. The selection of objective hubs must be meticulous to prevent the formation of isolated graphs resulting from the flow. In a network with n hubs and one base station, hub i is selected as the target for hub j based on conditions i * n+1, Euclidean distance (f) between nodes i and j, and data bandwidth (d). Ensuring the scientific rigor of the methodology, these steps facilitate the establishment of connections in a network, adhering to specified constraints and optimizing the allocation of hubs to enhance network performance. This approach mitigates the risk of creating isolated network segments and underscores the significance of criteria such as Euclidean distance and data bandwidth in hub selection.

Subsequently, commencing from the array's left side, identify the accessible source hub wherein the objective hub remains unmarked (i.e., designated as 0, indicative of an unestablished connection). Designate this hub as the source, iteratively executing the antecedent steps until a linkage with the base station is achieved. When a node concurrently serves as both the produced destination and the source node, the marker transitions from 0 to that new target node.. The search then resumes for the subsequent available source hub. This cycling of origin nodes persists until their eventual destinations are reached. The prescribed methodology to formulate a random graph of size 8 involves sequential steps. For instance, selecting node 2 as the source, linking it to node 6, and subsequently to node 8. Node 5 is subsequently chosen as the source, establishing a linkage with node 3, which, in turn, becomes the source for node 1. Upon tracking down the base station and confirming that objective hubs for all source hubs are identified, the random graph generation process is deemed complete. For a population size denoted as Pp, it becomes imperative to generate Pp instances of randomly generated graphs utilizing the aforementioned protocol. Subsequently, the fitness value for each individual is calculated before undertaking the initial selection process [17].

Fuzzy logic-based Genetic algorithm

The nodes within a Wireless Sensor Network (WSN) implement a decentralized clustering strategy grounded in fuzzy logic principles. In this network architecture, each node possesses an equal probability of serving as the Cluster Head (CH) or parent hub, reflecting the network's conceptualization as a tree structure. The fuzzy logic engine at each node in the CH selection process utilizes input parameters such as residual hub energy, hub distance to neighboring hubs, hub thickness, and bounce count. The fuzzy logic engine is strategically designed to consider solely the most pertinent nodes, those with the highest likelihood of assuming the role of CH.

In situations where a Sensor Node (SN) encounters a service disruption due to energy depletion, the Fuzzy Logic-based Genetic Algorithm (FLbGA) intervenes to ensure the seamless operation of the network. Performance evaluation of the FLbGA was conducted within a simulation environment, scrutinizing energy consumption, the count of active nodes, network lifespan, and the number of messages received within a five-node network. In alignment with energy conservation objectives and performance optimization, the FLbGA was specifically engineered to minimize message transmission, as articulated in prior studies [18,19].

Hybrid Fuzzy

Two predominant classes of hybrid optimization strategies in wireless sensor networks are discerned: fuzzy-based techniques and metaheuristic-based procedures. The inherent challenge arises from the exclusive selection of a single Cluster Head (CH) within the transmission range, leading to instances where certain nodes do not inherently assume CH status [20]. After a stipulated timeframe, each node autonomously designates a CH based on the relative signal strengths received from all prospective candidates. Subsequent to data collection and group formation facilitated by CHs adhering to predetermined guidelines, this section meticulously scrutinizes and contrasts the methodologies and attributes of fuzzy hybrid strategies across diverse research endeavors [21,22].

Sets and parameters

The deployed static sensors, denoted by the set I, are strategically positioned across a defined geographical region to facilitate mission objectives denoted as M. Each individual sensor i within the set I possesses an initial battery capacity represented by Vi. These sensors are designed to actively monitor and surveil objects within their respective fields of view, denoted by Zi, where Zi signifies any point within the coverage area of sensor i. The operational range of each sensor is characterized by a sphere of influence with a radius denoted as R.

Upon activation, the i sensor diligently monitors all targets within its coverage area, resulting in a discharge of its battery proportional to the surveillance efforts. Importantly, the battery life of the sensor remains unaffected during periods of inactivity. The collective surveillance area, denoted as Z, corresponds to the union of all individual coverage regions (⋃zi). To ensure the success of mission M, it is imperative that the lifespan of each sensor, denoted by the interval [Vminm, Vmaxm], falls within specified bounds. These bounds on battery life collectively contribute to the effective execution of the mission, underscoring the importance of careful energy management within the surveillance network.

Consider a set denoted as (f), representing a collection of objectives with indices ranging from 1 to (f), totaling (f) objectives. The standard notation for an objective's index is (f). Within the framework of planning a multisensor (ms) mission, the minimal duration dedicated to monitoring objective (j) is expressed as (Tmin, kms). The function (Ppf(t)) denotes the desired location of objective (j) at instant (t). Marks are categorized into two types: those entering a system and those exiting it. Incoming marks signify the date and time when a target initially enters a sensor's field of view, while outgoing marks indicate the date and time of a target's departure from that field. Conventionally, initial and final marks correspond to outgoing and ingoing directions.

Let J be a set encompassing all faces impacted by the shots, represented by indices {1...J}, with J indicating the total count of faces. If J serves as a hint for a face, its score is denoted as Jj. Each facet's time allocation adheres to the quality criteria of Dmin,km and Dmax,km throughout each kn time interval within every ms mission. The designated faces of interest are identified as J1...Jq, where J signifies candidate sensors covering a specific face.

The given framework establishes a comprehensive structure for characterizing objectives and faces within the context of a multisensor mission, incorporating precise notations and definitions to delineate the associated parameters and relationships.

In the context of mission planning, a value K: = {1...K} is assigned to each potential time window, where K denotes the total number of time frames, and (kn) represents the index of a specific time frame. By delineating a temporal interval between two points, a mission with m legs can be segmented into K discrete time windows. The fundamental principle underlying this variation involves treating the coverage of targets and faces equivalently. Specifically, deploying a sensor to cover a target is analogous to covering all locations within its coverage region and, consequently, all the facial marks corresponding to the target's placement. Focusing solely on the areas where targets are situated proves sufficient for their elimination.

To formalize this concept, a face-covering set, (J(kn)), is defined for each (k)-second interval. Given our knowledge of the faces containing each target, the original set of targets becomes unnecessary. This elimination of the target collection exemplifies one of the advantages conferred by face-based discretization. Given a mission duration (m), the scheduling parameter for each (kn)-minute interval is expressed as Δkn in milliseconds.

Optimizing the use of a sensor network is crucial, especially when considering future monitoring missions for the same organization [9]. The efficiency in current missions has implications for subsequent monitoring endeavors [9].

A set of missions, denoted as M=1...M, encompasses M total missions identified by the index ms. The completion of each m mission results in an i-fold decrease in sensor life expectancy. The cumulative time H is computed as the sum of all mission times, expressed as $H=\sum ms=1MHms=\sum ms=1M\sum kn=1K\Delta knms$.

4. Results from Computational Analysis

Consider the depicted scenario in the figures, featuring three sensors (I=03), two targets (J=02), seven-time windows (K=07), and three missions (M=03).

Figures 1 and 2 herein encapsulate the averaged outcomes resulting from an array of numerical experiments. To extend the operational lifespan of the sensor network, a meticulous analysis was undertaken, employing an optimal schedule for the activation or inactivation of each sensor. Consequently, the optimal solutions derived at the conclusion of this schedule predominantly pertain to the expected activation or inactivation instances within predefined time windows. This strategic approach contributes to enhancing the overall efficiency and longevity of the sensor network. These windows are characterized by their duration, along with the residual operational time on each sensor. The temporal alignment of sensor activations within specific intervals emerges as a pivotal optimal variable. In scenarios featuring three sensors, two targets, and seven temporal intervals, the strategic sequencing allows for the activation of fewer sensors. However, under different circumstances, where sensors are situated in an inaccessible location, it becomes economically judicious to deploy multiple missions within the same sensor network. This approach capitalizes on a contextual understanding of sensor accessibility and optimizes the allocation of resources.

optimizing life time WNS moving target

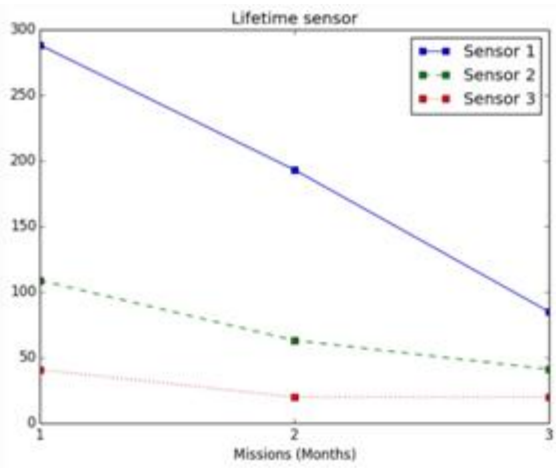

Fig 1 Mission lifetime sensor

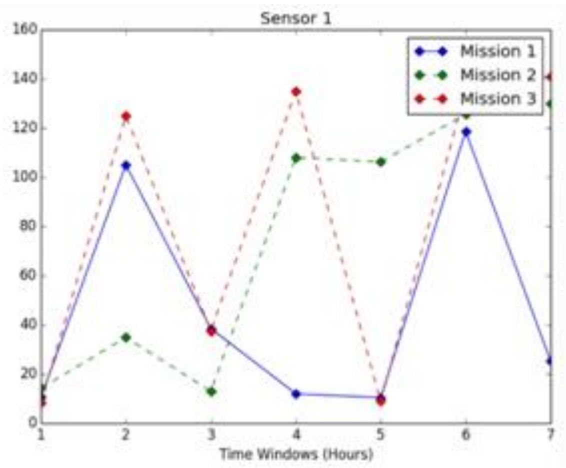

Fig 2 Time windows in hours- sensor 1

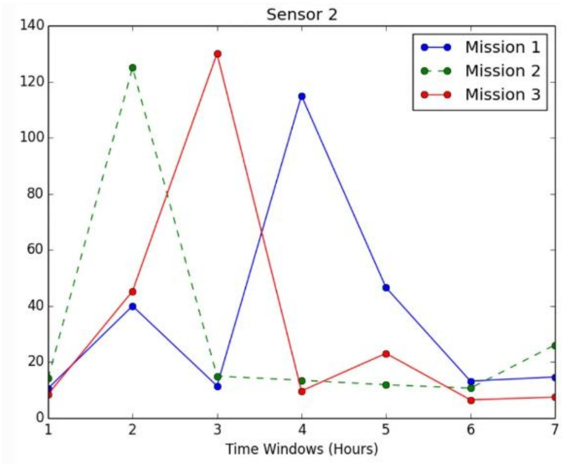

Fig 3 Time windows in hours- sensor 2

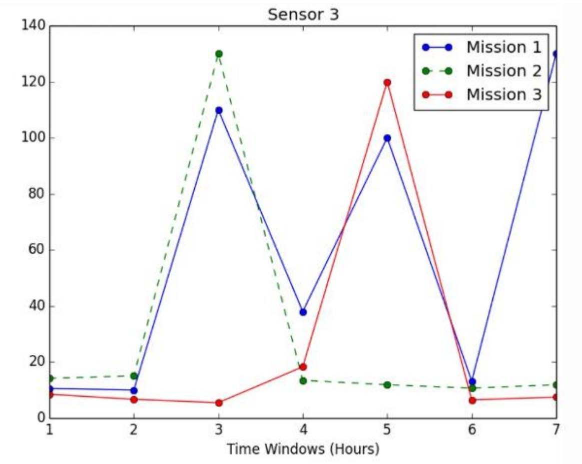

Fig 4 Time windows in hours- sensor 3

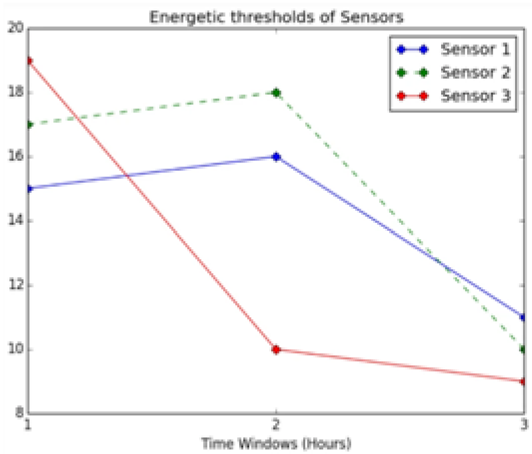

Fig 5 Time windows in hours- sensor 4

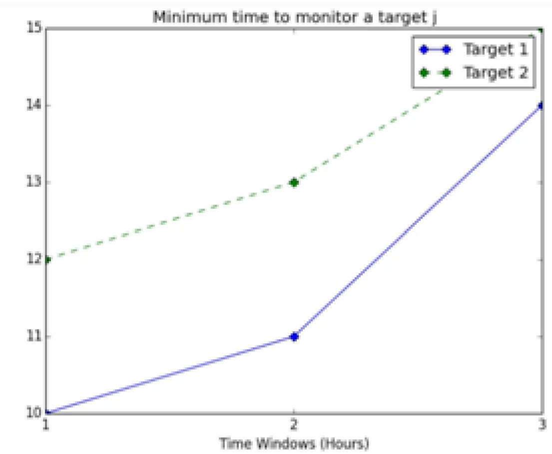

Fig 6 Time windows in hours- sensor 5

It is imperative to bear in mind that the simultaneous activation of all sensors is not requisite for comprehensive reconnaissance coverage within a designated zone across three sensors and seven temporal intervals spanning three missions. Each sensor is anticipated to activate during its designated operational timeframe, aligning with the arrival of targets within its operational domain. Authorized entities within this domain must be duly identified. In the absence of adversarial incursions within its field of vision, the sensor's vitality and operational capacity are replenished to an infinite extent. Exemplifying the process, during the initial mission, specifically in F1face and the first temporal frame, activation conventionally occurs at the mean requisite time of 100 Units.

Consequently, all sensors aligned with the specified side are momentarily suspended, directing their power reflections towards infinity. Consequently, the F2 face's primary sensor undergoes activation precisely half of the time across the entirety of three distinct missions and temporal intervals. To articulate succinctly, this strategic allocation extends the operational longevity of the sensor network by optimizing fewer sensors to cover larger spatial domains. Precise knowledge of the activation times for each sensor during each designated time interval on each face (denoted as Fk) within a mission becomes imperative for computing the aggregate time required for deploying a sensor over the entire mission duration (m).

For instance, the deployment of the F2 face's primary sensor during the second temporal interval aligns with the preconceived schedule, precisely timed at 87.5-time units. In a hypothetical scenario encompassing three sensors, eight temporal windows, and faces F1, F2, and F3, each sensor, on average, undergoes activation only four times per face across the seven-time windows. During sensor inactivity, its potential energy remains untapped, leading to an extended operational lifespan approaching infinity. This phenomenon highlights the efficiency and sustainability inherent in the utilization of the sensors within the specified temporal and facial parameters.

An additional consideration integral to the initiation process of the sensor involves the dichotomy between its active and inactive states within any given timeframe. Specifically, during the 8-second interval on side 1, the sensors remain inactive, whereas on side 2 during the same interval, all sensors are activated. It is imperative to meticulously discern the ingress and egress of each mark within every temporal span throughout a mission, facilitating scheduling optimization for enhanced target monitoring within specified areas of interest. For instance, in the context of the third mission with a singular target, the commencement involved a mark entering the initial timeframe, duly recorded by Cluster 3.

Assuming that marks represent decisions for each objective, knowledge of the primary tick enables the inference of subsequent marks across all temporal intervals. The primary objective of marks lies in determining, at each timeframe, whether an objective enters or exits a face, contingent upon the target's trajectory. This discernment enables the precise tracking of a target's movements, facilitating the impeccably sequenced actions of the sensor network. This imperative is particularly relevant when coordinating the activation of multiple sensors and targets, maintaining its validity even when the target's trajectory is subject to stochastic influences. This comprehensive understanding of sensor activation dynamics ensures the accurate orchestration of the sensor network, aligning with the scientific rigor inherent in such intricate systems.

The operational efficiency of sensor networks is intricately linked to the progressive deterioration of battery life with each successive flight. The foreseen pace at which sensors deplete their batteries enables the calculation of their remaining life post-flight. As illustrated in Fig. 3 & 4, a discernible decline in sensor life, quantified in energy units, is evident after each deployment. Consequently, the overall longevity of the sensor network hinges significantly on the rate of battery degradation. A discernible enhancement in the network's lifespan is observed with a diminishing degradation rate, underscoring the critical role of this parameter.

A pivotal consideration in maximizing mission effectiveness involves understanding the duration each sensor remains active during a given mission. Fig. 5 elucidates this aspect, highlighting that by discerning the duration of sensor usage in distinct intervals, a comprehensive assessment of each sensor's overall mission engagement can be ascertained. Notably, in missions with time frames exceeding 180 units, it becomes imperative for a sensor's operational lifespan to surpass or equal the cooperation threshold (i,m) for mission m. This criterion is crucial to avert potential disinterest in target monitoring mid-operation due to premature sensor depletion.

Ensuring the robustness of all sensors before mission launch is imperative to preempt the risk of sensor failure during critical operations. Figure 6 delineates the multifaceted constraints that sensors must satisfy for mission participation. Consequently, the initiation of subsequent missions is contingent upon the third sensor attaining the requisite 18-time units necessary for its participation in the ongoing operation. Moreover, an essential prerequisite involves establishing a guaranteed minimum time for target coverage by any selected sensors of interest.

In the context of subsequent missions, the designated time interval encompasses the minimum average duration essential for error-free and accurate target monitoring. This meticulous consideration of sensor health, engagement duration, and coverage prerequisites aligns with the overarching objective of optimizing mission outcomes in sensor network operations.

5. Conclusion

To optimize the temporal utilization of a network of sensors, a mixed variable linear programming model was meticulously developed. This model relies on discrete marks denoting the initiation and termination of each temporal frame, strategically determining the precise timing of target positioning throughout the mission. The primary objective is to strategically plan the activation and deactivation of sensors within the network, aiming to maximize their lifespan during each mission. This proactive approach facilitates the identification of sensors crucial for engagement during specific time windows, precisely aligning with predetermined tasks. Additionally, we conducted a comprehensive analysis to ascertain the minimum energy requirements for a sensor's active participation in a mission and the speed at which the sensor network can track and intercept a moving object. These determinations contribute to a comprehensive understanding of the operational dynamics, enabling the establishment of minimum monitoring durations, commonly referred to as the "guarantee of coverage," and defining the threshold criteria for a sensor's involvement in a mission. In essence, our devised strategy ensures the longevity of the sensor network throughout missions, a significant departure from conventional methods. Unlike existing methodologies, our approach leverages a substantial number of sensor networks. This strategic sequencing allows for the activation of a select subset of sensors necessary for a mission involving two targets and spanning seven distinct time periods. This selective activation maximizes the overall utility of the sensor network and optimizes the operational life of individual sensors. Furthermore, energy efficiency improvement in Wireless Sensor Networks (WSNs) through the optimization of clustering strategies is a well-established practice. Recent advancements in hierarchical optimization strategies for cluster head selection, cluster formation, data aggregation, and communication were subjected to detailed scrutiny. These clustering methods, categorized based on their optimization techniques such as meta-heuristics, fuzzy logic, or a hybrid of both, were systematically reviewed. Comparative analyses were conducted across these categories, considering metrics like performance, clustering success, and optimization parameters.

The examination of various clustering protocols encompassed critical aspects, goals, and benefits associated with each procedure. Simulations were executed using platforms like JPAC, MATLAB, and NS, allowing for the comparison of protocol performances. Key criteria such as cluster head parameters, rotation, data transmission techniques, mobility, and deployment strategies were scrutinized specifically within fuzzy-based protocols. Results were methodically analyzed to draw meaningful parallels, confirming the optimization of parameters. Notably, our study contributes a comprehensive map for future research endeavors in the domain of cluster networks. The synthesis of our findings not only advances the understanding of temporal optimization in sensor networks but also propels the discourse on enhancing energy efficiency in WSNs through sophisticated clustering methodologies. The established insights offer a roadmap for researchers, guiding their focus toward innovative solutions and advancements in this dynamic field.

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