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Tradeoff Between Sensing Quality and Network Lifetime for Heterogeneous Target Coverage Using Directional Sensor Nodes

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***Abstract*—Conventional researches on target coverage in Directional Sensor Networks (DSNs) mainly focus to increase the network lifetime, overlooking the coverage quality of targets, especially they don't consider the targets that have heterogeneous coverage requirements. Increasing sensing quality is of the utmost importance to ensure comfort living in Smart Cities. In this paper, we have designed a generalized framework, namely MQMS-DSN (Maximizing coverage Quality with Minimum number of Sensors in DSN), that has the ability to maximize the target coverage quality or the network lifetime or to make an efficient tradeoff in between the two following application demand. Using a probabilistic model for measuring the sensing coverage quality, we have developed optimal, suboptimal and greedy solutions for MQMS problem. Empirical evaluations of the proposed MQMS systems have been carried out in Network Simulator version 3 (ns-3). The results show the effectiveness of the proposed systems compared to state-of-the-art-works in terms of sensing quality and network lifetime.**

***Index Terms*—Sensing coverage quality, Network lifetime, Directional sensor, Heterogeneous target.**

I. INTRODUCTION

Directional Sensor Networks (DSNs) are proven to provide better network lifetime and sensing coverage compared to their omni-directional counterpart [1], [2], [3]. These two cutting-edge features help DSNs attracting interests of research and industrial communities, particularly for the areas of high quality sensing in Smart City applications including health-care, infrastructure security, traffic and access monitoring, etc. [1], [4]. Designated targets in Smart City are monitored to ensure more privileged and smarter living environments for the dwellers.

Target coverage is one of the fundamental research problems in DSNs, where a large number of sensors are dropped to monitor dispersed targets of interests within a given terrain. Conventional researches on target coverage mainly focus to enhance the network lifetime ensuring continuous monitoring of as maximum targets as possible [2], [5], [6]. However, in reality, distinct targets may have different significance and their required coverage qualities might differ from each other [7], [8], [9], [10]. Providing heterogeneous sensing qualities to all the targets in the network throws the following two major challenges that are to be carefully addressed.

1) **Coverage quality**: Traditional researches on target coverage have been carried out based on binary disk model [5], [6], [11], [12], [13], [14] where a target is said to be covered by a sensor if the former is located within sensing range of the later. However, the quality of sensing of a target may vary due to many reasons including the exact distance between the target and the sensor, the rate of signal attenuation [9], [10], [15] etc. In [9], [10], [16] sensing quality is quantified by an inversely proportional function of distance between a sensor and a target. The authors in [15] determined the sensing coverage quality as a function of signal attenuation factor. In reality, sensing quality is imprecise and inhomogeneous and mostly follows probabilistic model [11], [17], [18] and thus a more realistic measurement might boost up the system performance. Besides, it is also noticeable that, for some applications (e.g., emergency rescue operation), we need to focus on enhancing the coverage quality. Nevertheless, achieving high quality sensing requires to engage more number of nodes in the operation that consequently decreases the network lifetime.
2) **Network lifetime**: Many works in the literature focused on strategies to maximize the network lifetime. As far as sensing quality is concerned, the problem is transferred to maximize the network lifetime ensuring the required quality of each targets. In [10], nodes of the network are divided into non-disjoint cover sets so that each set maintains the required coverage quality of the targets. Then, the scheduling of the cover sets are optimized in such a way that the network lifetime is maximized. Similarly, in [15], the network lifetime is maximized through optimal choosing of non-disjoint cover sets that can ensure minimum sensing quality for the targets. In addition to formulating MILP (Mixed Integer Linear Programming) to achieve optimal solution, heuristic or greedy solutions are also developed in [10], [15]. However, these works mainly focus on network lifetime, overlooking the enhancement of quality. From the graphs of Figure 1, we observe that an inverse relationship

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exists between quality and lifetime. The reason is that, extended network lifetime requires to keep the number of active nodes as less as possible. On the contrary, if we try to increase the quality, it hinders to enhance the network lifetime. Therefore, an efficient solution is needed to address both the quality and lifetime that can reflect the true demands of the applications.

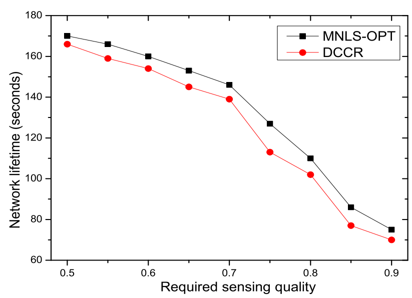

Fig. 1. Impacts of sensing quality on network lifetime (Experiments are conducted in NS-3 [19] with area = 100m × 100m, sensor nodes = 100, sensing radius = 25m, target = 20, sensing sector = 4)

Based on the above observations, in this study, we explore the following research questions, develop optimal and sub-optimal greedy solutions and present the analytical results.

- How to maximize the target coverage quality while ensuring balanced energy consumption among the sensor nodes?
- What strategies can further optimize the network lifetime while satisfying the required sensing coverage qualities for all targets in the terrain?
- How to schedule and re-schedule the sensor nodes and their sensing directions so as to make an efficient tradeoff between the sensing coverage quality and network lifetime?
- What measurement methodology is more effective for maximizing the sensing qualities of targets?

We observe that, focusing on only coverage quality or network lifetime without considering both, failed to reflect the actual requirements of diverse applications. Applications may require to give emphasis on enhancing coverage quality or network lifetime or both based on the significance of the application. For example, an emergency rescue operation may need high coverage quality; on the other hand, remote monitoring of elderly people at home using multimedia sensor networks may demand longer network lifetime maintaining a certain coverage quality [20], [21]. We also find that, if the residual energy and the coverage quality are not considered jointly, it is difficult to achieve enhanced network lifetime since the energy depletion rates of different sensor nodes vary greatly from each other.

In this paper, we develop a general framework, namely MQMS-DSN (Maximizing Coverage Quality with Minimum Number of Sensors in DSN), that is applicable to maximize the target coverage quality or the network lifetime or to make an efficient tradeoff between the two following application demands. The proposed MQMS-DSN framework is a Mixed Integer Linear Programming problem (MILP) that facilitates to achieve multiple objectives by using a suitable tuning parameter. A preliminary version of this work has published in [22] where, optimal coverage strategy and evaluation were only presented. Indeed, obtaining the optimal solution is a combinatorially hard problem to solve as the basic target coverage problem is NP-hard [6], [10]. Thus, to obtain meaningful insights and overcome the complexity of the original problem, we provide sub-optimal and greedy heuristic solutions for clustered DSN. Each cluster head (CH) takes coverage decisions independently following current situations of its vicinity. Measuring the coverage quality using a probabilistic sensing model (i.e., Elfes probabilistic model [18]), the residual energy-aware selection of active nodes helps our MQMS-DSN formulation to achieve enhanced network lifetime. We also present schemes to mitigate the redundancy of active nodes for common covered targets by inter-cluster communications. Finally, the performance results of the proposed solutions, carried out in NS-3 [19], show that the proposed MQMS-DSN outperforms state-of-the-art-works in terms of network lifetime, coverage quality, percentage of active sensor nodes, and standard deviation of residual energy.

The rest of this paper is organized as follows. We have described related works and motivation in Section II. The network model is described in Section III and our proposed MQMS-DSN architecture is detailed in IV. In Section V, the simulation results are presented and finally, we have concluded the paper in VI.

II. Related Works

Now-a-days, the sensing coverage problem in DSNs has received immense interests from both industrial and academic communities. Studies related to coverage field have some subcategories: (1) area coverage [1], [23], [24], [25] (2) target coverage [2], [6], [10], [13], [26] and (3) sensing or barrier coverage [1], [27]. Our contributions in this work are related to the field of target coverage, where main focus is to increase the quality of coverage for some specific targets while prolonging the network lifetime.

In literature, a good number of studies have addressed the target coverage issue for directional sensors assuming all targets have equal importance [2], [6], [13], [28], [29], [30]. The authors of [13] are the pioneer for addressing target coverage problem in DSNs that presents solutions to the problem of covering maximum number of targets with minimum number of sensors, namely MCMS problem. In [5], [6], Cai et al. address the target coverage problem by developing multiple directional cover sets (MDCS) that are non-disjoint so as to extend the network lifetime. In [28], a greedy approximate algorithm is proposed to solve the maximum directional sensor coverage (MDSC) problem. To further maximize the number of covered target points, they also develop an MKDSC (maximum K directional sensor coverage) algorithm by selecting and assigning directions for a subset of K sensors. The authors in [29] have studied the problem of minimizing the total energy costs for both sensing and connectivity, termed as the Minimum-Energy Connected Coverage (MeCoCo) problem. Learning automata based near-optimal solutions for the target coverage problem are developed in [31], [32]. The authors of [2] first exploit the cluster heads (by forming a clustered network) to greedily activate the minimum number of member sensor nodes that can cover all targets in the network in a distributed way.

In [33], Fusco et. al. have studied the problem of selecting a minimum number of sensors and assigning orientations such that the given area (or set of target points) is k-covered (i.e., each point is covered k times). For the NP-hardness of the problem, a simple greedy algorithm is also designed to reduce the computation complexity. In target Q-coverage (TQC) [34], coverage sets of directional sensor nodes, that satisfy the coverage quality requirement, are developed to employ each of those independently so that the network lifetime is extended. However, the coverage sets don't guarantee continuous monitoring of targets; rather, they can be served with tolerant service delay. Lu at. el. further advance the solution to Q-coverage problem by scheduling multiple sensors to cover a certain target at sporadic times but ensuring coverage by at least one sector in a given time period [35]. All the works, studied above, are based on binary disk model [11], [12], i.e., a sensor node covers a target with probability 1 if the target resides within the sensing range, 0 otherwise. However, this is sometimes impractical because sensing quality mostly follows probabilistic nature [18]. A probabilistic sensing model (details are in section III) is more appropriate as the phenomenon being sensed, sensor design and environmental conditions are all stochastic in nature.

The sensing coverage quality is defined as a function of received signal strength in [15] and distance in [9], [10], [16]. In [15], Jong et. al. have addressed the coverage maximization problem by developing optimal cover sets using directional sensor nodes. In [9], the authors compute utility values for the targets under sensing in order to satisfy the required quality for all targets by developing an optimal subset of directional sensors using genetic algorithm. In [10], the authors first formulate the coverage problem as Maximal Network Lifetime Scheduling Problem (MNLS) considering the coverage quality as a function of distance between the sensor and the target. The key philosophy of the solution is to form non-disjoint sets of sensor directions, named as feasible cover sets, and to make an optimal scheduling of the cover sets that maximizes the network lifetime while meeting the coverage requirements of individual targets. Due to the NP-hardness of the optimal formulation, later they also provide centralized greedy based solution. Hosein et. al., in [16], have assumed that each target has different coverage quality requirement and constructed maximum number of cover sets, that satisfy the required quality, and developed a learning-automata based scheduling algorithm for the cover sets so that the network lifetime is maximized.

In this work, we put forward a good number of contributions in the literature compared to the existing state-of-the-art works [9], [10], [16]. Firstly, we introduce the probabilistic sensing model to quantify the coverage quality of targets in DSNs, opposing to traditional distance based methods in the above works. Secondly, we develop a generalized framework to the problem of target coverage in DSNs that can be tuned to a solution for the coverage quality maximization or lifetime maximization problem while keeping the required coverage quality or a tradeoff can be made between the two; whereas, [9], [10], [16] focused only to maximize the network lifetime maintaining the required coverage quality of targets. Thirdly, a cluster-based distributed solution to the target-coverage problem in our proposed MQMS-DSN systems mitigates the scalability problem of the above fully centralized solutions. Finally, unlike [9], [10], [16], the proposed MQMS-DSN systems selects sensor nodes having higher residual energy to cover targets, enhancing the network lifetime significantly.

III. System Model and Assumptions

A. Network Model

We consider a Directional Sensor Network (DSN) consisting of a set $\mathcal{N}$ of large number of stationary directional sensor nodes in a 2-D Euclidean plane. A set $\mathcal{M}$ of targets with known locations is also positioned in the same terrain. Sensor nodes are randomly deployed maintaining large density to achieve high coverage ratio. We also assume a sink node is located at a fixed point in the terrain for collecting data from sensor devices through multi-hop data communication. We also consider that, in terms of number of communication and sensing sectors, corresponding radius and initial energy E_o, all nodes are homogeneous. However, individual targets $m \in \mathcal{M}$ have different sensing coverage quality requirements, $\varrho(m)$. We also assume that each sensor node is aware of its location and its neighbors by using GPS or any other localization method [36]. The tasks of sensing and transmission are directional and the reception is omni-directional for the nodes.

To support implementations of sub-optimal and greedy alternate solutions to our optimal MQMS-DSN problem, we also assume that the network nodes are clustered. That is a suitable clustering algorithm [2], [37], is running in the network that selects cluster heads (CHs) and gateways (GWs) to develop a communication backbone for the network. Let $\mathcal{N}_k$ denotes the set of member nodes of a CH k, $k \in \Upsilon$. In the literature, a very good number of clustering algorithms exist that consider the coverage problem for omni-directional sensor networks [38], [39]. Nevertheless, those are not applicable for directional sensor networks since there are some basic differences between the operational procedures of omni and directional sensor nodes. In the state-of-the- art works, we have found two leading clustering techniques that work with directional sensor networks - ACDA [37] and TCDC [2]. In autonomous clustering algorithm (ACDA) [37], individual nodes exchange messages for a random waiting time period to select cluster heads and gateway nodes. At the beginning, ACDA does not consider residual energy levels of nodes; however, later it renews the cluster heads and gateways studying the residual energy levels. On the other hand, the TCDC [2] selects a node as cluster head (or gateway) considering its residual energy level, number of neighbor nodes and its distance from the sink. The renew process is performed by existing CHs and gateways when their energy levels fall below a certain threshold. Both the ACDA and TCDC systems use gateways to route data packets from CHs toward the sink using the shortest hop single path routing strategy. The performances

TABLE I
LIST OF NOTATIONS

Symbol	Definition
$\mathcal{N}$	Set of all sensor nodes in the network
$\mathcal{M}$	Set of all targets in the network
θ_s, R_s	Sensing angle and radius
Ω	The set of sensing sectors of a node, $\|\Omega\| = \frac{2\pi}{\theta_s}$
ϕ_i	The set of directions of sensor i, $\phi_i = \{< i, \omega > \mid \omega \in \omega\}$
Ψ	The set of directions of all the sensors, $\Psi = \cup\, \phi_i,\ \forall i \in \mathcal{N}$
$\varrho(m)$	The sensing coverage quality requirement for target $m \in \mathcal{M}$
$\sigma_{i,\omega}(m)$	Given sensing coverage quality for target $m \in \mathcal{M}$ by sector ω of node i
$\sigma(m)$	Aggregated sensing quality for target $m \in \mathcal{M}$
$\vec{V}_i^{\omega}$	Working direction of a node i in sector ω
Υ	Set of all cluster heads
$\mathcal{N}_k$	Set of member nodes of CH $k \in \Upsilon$
$\mathcal{M}_{i,\omega}$	Set of targets for which the sensing coverage quality value $\sigma_{i,\omega}(m_k) \neq 0$ in the sensing sector ω for node i
$\mathcal{M}_k$	Set of targets covered by member nodes of a CH k i.e., $\mathcal{M}_k \leftarrow \cup\, \mathcal{M}_{i,\omega}, \forall i \in \mathcal{N}_k, \forall \omega \in \Omega$
Γ_k	Set of one hop neighbor CHs of CH k

of the proposed suboptimal and greedy MQMS solutions may vary depending on the clustering technique. However, previous study reveals that, TCDC outperforms between the two and thus we carry out performance evaluation using TCDC [2] as underlying clustering algorithm. Throughout the paper, we have adopted the notations described in Table. I.

B. Sensing Models

Each sensor has a set Ω of non-overlapping sensing directions (Fig: 2(a)), where each direction of a node is a sector of a disk centered at the sensor with sensing radius R_s and angle $\theta_s = \frac{2\pi}{|\Omega|}$. The directional vector $\vec{V}_i^{\omega}$ represents a center line on the sensing sector $\omega \in \Omega$. To determine the presence of a target $m \in \mathcal{M}$ in sector ω of node i, we use the target in sector (TIS) test [1], [13], [40] and thus build a set χ_m that contains the tuple $< i, \omega >$ for all nodes that can cover the target as follows,

$$\chi_m \leftarrow \{< i, \omega > \mid d(i,m) \leq R_s,\ \vec{im}.\vec{V}_i^{\omega} \geq d(i,m)\cos\frac{\theta_s}{2}\}, \tag{1}$$

where, $d(i,m)$ is the Euclidean distance between the node i and target m. Depending on the sensing range R_s, an individual sensor node is able to sense only a subset of the observing area, where it is deployed.

C. Sensing Coverage Quality Measurement

Unlike binary disk model [11], [12], [13], the quality measurement for a target offered by any node in probabilistic model [11], [17], [18], depends on the observing region of the node where the target is located. According to Elfes model [11] [17] [18], the probabilistic sensing quality $\sigma_{i,\omega}(m)$ for a target $m \in \mathcal{M}$ covered by a node i in sector ω can be calculated as follows,

$$\sigma_{i,\omega}(m) = \begin{cases} 0 & R_s + R_u \leq d(i,m),\ < i,\omega > \in \chi_m, \\ e^{-\lambda\alpha^{\beta}} & R_s - R_u < d(i,m) < R_s + R_u,\ < i,\omega > \in \chi_m, \\ 1 & R_s - R_u \geq d(i,m),\ < i,\omega > \in \chi_m, \end{cases} \tag{2}$$

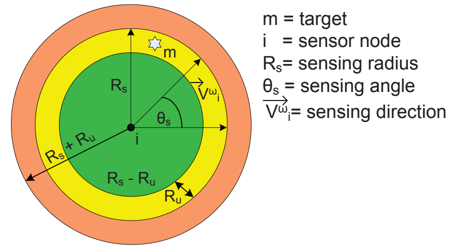

Fig. 2. Probabilistic sensing model

where, $R_u (\leq R_s)$ is the measure of sensing uncertainty of a target; $\alpha = d(i,m) - (R_s - R_u)$, β and λ are parameters $(0 \leq \beta, \lambda \leq 1)$ that measure detection probability when a target is at distance greater than R_u but within R_s (Fig: 2(a)). Therefore, the aggregated sensing coverage quality of a target m offered by all nodes in the vicinity is measured by,

$$\sigma(m) = 1 - \prod_{< i,\omega > \in \chi_m} (1 - \sigma_{i,\omega}(m)). \tag{3}$$

Our proposed MQMS-DSN system aims to maintain the required sensing coverage quality, *i.e.*, keeping $\sigma(m) > \varrho(m)$, for all targets $m \in \mathcal{M}$ in the network by activating different sensors in certain directions.

IV. PROPOSED MQMS-DSN SYSTEMS

In this section, at first, we develop a centralized optimal MQMS-DSN system, namely CMQMS, which is a generalized framework for either maximizing the network lifetime while supporting the required coverage quality or maximizing the coverage quality only or orchestrating a tradeoff between the two. Then, we develop a suboptimal system (SMQMS) for a clustered network to enhance the scalability of the solution, where each cluster head decides the activation of member nodes and their sectors in distributed way. Finally, GMQMS is proposed that greedily chooses the sensor nodes so as to increase either the coverage quality or the network lifetime. What follows next, we explore the operation of the aforementioned MQMS-DSN systems in detail.

A. Centralized Optimal MQMS-DSN System

The CMQMS system is formulated as a Mixed Integer Linear Programming (MILP) problem, where a central controller chooses the nodes that provide optimal performances. The central controller (sink node) first generates candidate sets, consisting of some nodes and their sectors, that meet the required coverage quality, as described below.

1) Formation of Coverage Candidate Sets: Let Ψ be a set of tuples $< i, \omega >$ for all sensors $i \in \mathcal{N}$ and for all directions $\omega \in \Omega$. A *candidate set* ψ is a subset of Ψ that can satisfy the required coverage quality $\varrho(m)$ of all targets $m \in \mathcal{M}$ in the network. We define a boolean variable $b_{i,\omega}$ that represents whether a tuple $< i, \omega >$ is present in a candidate set or not; the value is determined as,

$$b_{i,\omega} = \begin{cases} 1 & \text{if } < i,\omega > \in \psi,\ i \in \mathcal{N},\ \psi \subseteq \Psi\ , \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Algorithm 1 Formation of Coverage Candidate Sets

INPUT: Set Ψ' of tuples $< i, \omega >$ for nodes $i \in \mathcal{N}$
OUTPUT: Candidate sets $\psi \subseteq \Psi'$

1. $\Psi \leftarrow \Psi \setminus \; < i, \omega >$, where the tuple $< i, \omega >$ can't cover any target $m \in \mathcal{M}$
2. $\Psi \leftarrow \; \Psi \setminus < i, \omega > \; for \; E_r(i) \leq E_{th}$
3. $\Psi' \leftarrow \phi$
4. **for all** $\psi' \subseteq P(\Psi)$ **do**
5.   **if** $(|\psi'| \leq |\mathcal{N}|$ AND $\sum_{<i,\omega>\in\psi} b_{i,\omega} \leq 1)$ **then**
6.   **if** Eq. 5 returns TRUE for ψ' **then**
7. $\psi \leftarrow \psi'$
8. $\Psi' \leftarrow \Psi' \cup \psi$
9.   **end if**
10.   **end if**
11. **end for**

Note that, a node i can't exist multiple times in a particular candidate set, $\psi \in \Psi$. Many such coverage candidate sets can be formed in the network, where the elements in the set altogether satisfy the condition in Eq. 5.

$$1 - \prod_{<i,\omega>\in\psi} (1 - \sigma_{i,\omega}(m)) \geq \varrho(m), \quad \forall m \in \mathcal{M} \tag{5}$$

The complete process of forming coverage candidate sets is presented in Algorithm 1. In line number 1, we filter out the tuples $< i, \omega >$ that can't cover any target, helping us to reduce the complexity of the algorithm. The complexity of the algorithm can further be lessened by sieving out the nodes that have residual-energy smaller than a threshold value (E_{th}), as depicted in line 2. In line numbers 4-10, in each iteration, we take a subset ψ' from the power set, $P(\Psi)$, and test whether it can satisfy the required coverage quality using Eq. 5, whether the subset contains no more than one $< i, \omega >$ entries for a single node i and whether the cardinality of the subset limits within the size of the network or not. In the case, all the above conditions return true for a subset ψ', it is declared as a candidate set $\psi \in \Psi'$, where Ψ' is the set of all coverage candidate sets.

The complexity of this algorithm is quite straightforward to follow. The lines 4-10 are enclosed in a loop which iterates at most $2^{|\mathcal{N}|\times|\Omega|}$ times having a computational complexity of $O\big(2^{|\mathcal{N}|\times|\Omega|}\big)$. Here, $2^{|\mathcal{N}|\times|\Omega|}$ is actually the computational complexity of generating the subsets. The rest of the lines have constant time unit complexities. Therefore, to formulate the candidate sets the overall time complexity is $O\big(2^{|\mathcal{N}|\times|\Omega|}\big)$.

2) MILP Formulation: Out of the competent coverage candidate sets, the proposed CMQMS system finds an optimal set ($\psi^* \in \Psi'$) that achieves our goals through exploring all possible ways using an MILP optimization function, expressed as follows,

$$\underset{\psi\in\Psi'}{arg\ min}\Bigg\{\gamma \times \sum_{<i,\omega>\in\psi} b_{i,\omega} \;-\; (1-\gamma)\times \sum_{m\in\mathcal{M}} \Big(1 - \prod_{<i,\omega>\in\psi} \big(1 - \sigma_{i,\omega}(m)\big) b_{i,\omega}\Big)\Bigg\} \tag{6}$$

subject to,

$$\sum_{\omega\in\Omega} b_{i,\omega} \;\leq\; 1, \quad \forall < i, \omega > \in \psi, \; \psi \in \Psi' \tag{7}$$

$$1 - \prod_{<i,\omega>\in\psi} (1 - \sigma_{i,\omega}(m)) b_{i,\omega} \geq \varrho(m), \quad \forall \; m \in \mathcal{M} \tag{8}$$

$$E_{th} \leq E_r(i) \;\leq\; E_o(i), \quad < i, \omega > \in \psi, \; \psi \in \Psi' \tag{9}$$

$$0 \leq \gamma \leq 1. \tag{10}$$

The constraint (7) ensures that a node can participate in at most one sector in a particular candidate set. The constraint (8) satisfies the coverage quality constraint, i.e., all targets are covered with required coverage qualities by the sensors in the candidate set. A node is activated only if its residual energy $E_r(i)$ is larger than a threshold value E_{th}, implemented by the constraint (9). The constraint (10) sets the value of the tuning parameter γ. Therefore, based on the constraints, the objective function finds an optimal candidate set for activation that can maximize the aggregated coverage quality of targets (when $\gamma = 0$) or the network lifetime (when $\gamma = 1$) or make a trade off in between the two, depending on the value of $0 < \gamma < 1$. In other words, the proposed objective function, depicted in Eq. (6), implements a generalized framework. In the case $\gamma = 0.5$, both the performance metrics- coverage quality and network lifetime get equal importance; the network lifetime can be given more priority by setting $0.5 < \gamma < 1$ while maintaining the minimum coverage quality for targets and the reverse case happens when $0 < \gamma < 0.5$.

In the above MILP formulation, the central controller finds a set ψ^* and activates the nodes to their corresponding sectors, $< i, \omega > \in \psi^*$. However, producing only one optimal set does not guarantee enhanced lifetime; we have to rotate the responsibilities among other nodes so as to increase the network lifetime. The central controller initiates generation of a new optimal set ψ^{**} when the following condition holds true for any active node $i \in \mathcal{N}$,

$$E_r(i) \leq E_{th}, \quad < i, \omega > \in \psi^*. \tag{11}$$

Note that the value of energy threshold E_{th} is not kept fixed; rather, its value is updated using Eq. 12 every after running the objective function, where, the weight parameter $0 < \zeta < 1$ allows new nodes to come into the optimal candidate set.

$$E_{th} = \zeta \times E_{th} \tag{12}$$

Now, the key limitation of the proposed CMQMS system is that it requires all nodes in the network to send their instantaneous status (location, residual energy, etc.) to a central controller (typically, a sink); it is very expensive in terms of computation and communication costs as the number of targets and nodes is increased. Furthermore, the CMQMS is an NP-Hard problem and thus polynomial-time solution for CMQMS

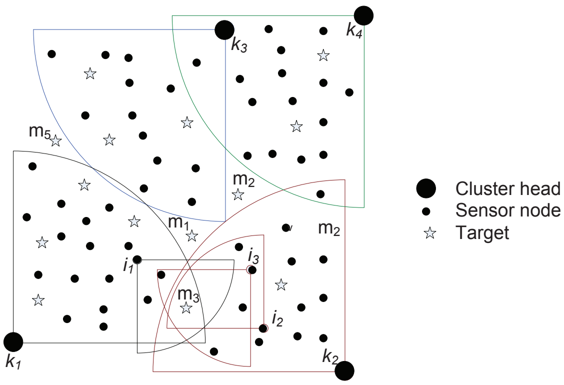

Fig. 3. Target coverage by member nodes of cluster heads

often will not be possible, like that in [9], [10]. What follows next, we present a suboptimal system for covering targets.

B. Distributed Sub-optimal MQMS-DSN System

In this section, we develop a sub-optimal MQMS system, namely SMQMS, that distributes the responsibility of running target coverage algorithm to many nodes in the network, unlike at a central node in CMQMS system. The key philosophy is to divide the network into many clusters, where each cluster head (CH) is given the duty to select a set of active nodes and their sensing sectors so as to maximize the coverage quality with minimum number of sensors. One naive solution is to run the same objective function (i.e., the Eq. 6) at CHs as if a CH acts like a central controller for reduced set of sensors and targets located within its working communication sector. However, it introduces some new challenges to achieve our goals:

- *Some targets may remain uncovered*- Targets located in void zones (i.e., not located within the communication range of any of the CHs in the neighborhood) will not be covered. For example, the targets m_1, m_2 and m_5 are out of the communication boundaries of CHs and they might not covered by any of the CHs, as shown in Fig. 3. This is happened due to the reduction of visibility on the network by individual CHs and participation of only sensor nodes in cluster formation process without considering target locations [2], [37].
- *Redundant activation of sensors*- As individual CHs are activating their sensor nodes for covering targets within their communication regions, a target (located at boundary zones) may be covered by excessive sensor nodes than it requires. For example, in the Fig. 3 suppose, alone the node i_1 or nodes i_2, i_3 jointly can satisfy the sensing requirement of target m_3. If CHs k_1 and k_2 work independently, the activation of all the three sensors are unnecessary here.

To mitigate the above challenges, we reformulate the previous MILP (in Eq. 6 to 10) to develop the sub-optimal MQMS-DSN system. Note that, we can mitigate the first problem neither by including targets in the cluster formation process nor compelling those to be located within the communication region of any of the CHs, since it's not realistic. Therefore, we redefine the set of targets, $\mathcal{M}_k$, that will be considered by a CH $k \in \Upsilon$ as,

$$\mathcal{M}_k = \bigcup_{\forall i \in \mathcal{N}_k} \mathcal{M}_{i,\omega}, \quad \forall \omega \in \Omega \tag{13}$$

where, $\mathcal{N}_k$ is the set of member nodes of CH k and $\mathcal{M}_{i,\omega}$ is the set of all targets covered by a sensor node i focused in direction $\omega \in \Omega$, defined as, $\mathcal{M}_{i,\omega} = \{m \mid m \in \mathcal{M}$ and $\sigma_{i,\omega}(m_k) \neq 0\}$. This redefinition of the target set, at different CHs, ensures that, every target in the terrain must be a member of any of target sets $\mathcal{M}_k,\ k \in \Upsilon$, as proved in Lemma 1.

To address the second challenge, *i.e.*, redundant activation of sensor nodes, we allow a CH to share the set of targets that are already covered by it along with their one hop neighbor CHs, Γ_k, after each time it selects a set of sensors for covering the targets. Like in CMQMS system, a SMQMS CH k calculates the values, $\sigma(m)$ and $\sigma_{i,\omega}(m)$ using Eq. 1 to Eq. 3 $\forall m \in \mathcal{M}_k$ and generates a set of candidate sets $\Psi'_k = \{\bigcup \psi \mid <i,\omega>\in \psi,\ \forall i \in \mathcal{N}_k\}$ using Algorithm 1. The MILP for the SMQMS system is reformulated as follows,

$$\underset{\psi_k \in \Psi'_k}{arg\ min}\left\{\gamma \times \sum_{<i,\omega>\in\psi_k} b_{i,\omega} - (1-\gamma)\times \sum_{m\in\mathcal{M}_k}\left(1 - \prod_{<i,\omega>\in\psi_k}\left(1-\sigma_{i,\omega}(m)\right)b_{i,\omega}\right)\right\} \tag{14}$$

subject to,

$$\mathcal{M}_k = \mathcal{M}_k \setminus \mathcal{M}_l, \quad \forall l \in \Gamma_k, \tag{15}$$

$$\sum_{\omega\in\Omega} b_{i,\omega} \leq 1, \quad \forall <i,\omega> \in \psi_k,\ \psi_k \in \Psi'_k \tag{16}$$

$$1 - \prod_{<i,\omega>\in\psi_k} (1-\sigma_{i,\omega}(m))b_{i,\omega} \geq \varrho(m), \quad \forall\ m \in \mathcal{M}_k \tag{17}$$

$$E_{th} \leq E_r(i) \leq E_o(i), \quad <i,\omega>\in \psi_k,\ \psi_k \in \Psi'_k \tag{18}$$

$$0 \leq \gamma \leq 1. \tag{19}$$

Here, the constraint (15) helps the SMQMS system to minimize redundant coverage of targets, *i.e.*, it further minimizes the active number of sensor nodes in a neighborhood. The rest of the constraints (16), (17), (18) and (19) follow the similar interpretation as before but for reduced set of sensors $i \in \mathcal{N}_k$ and targets $m \in \mathcal{M}_k$.

Lemma 1: *The distributed SMQMS system can offer the required coverage quality for all targets in the terrain as maintained by the CMQMS system.* □

Proof: We show the correctness of the lemma *using proof by contradiction*. We first assume that, after execution of SMQMS system, there remains a target $m \in \mathcal{M}$ in the network, which is not covered by its required quality.

Note that, the required coverage quality $\varrho(m)$ of a given target $m \in \mathcal{M}$ in the network may not be fulfilled if any of the following two conditions holds true:

(a) Sufficient number of sensor nodes are not available in the network to satisfy the coverage quality of the targets.
(b) The given target is not visible by the entity executing the sensing coverage algorithm.

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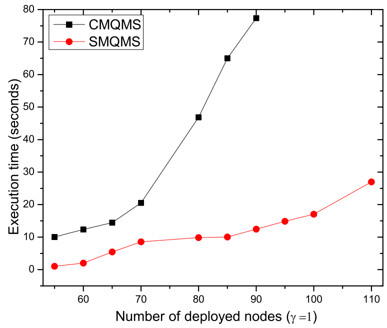
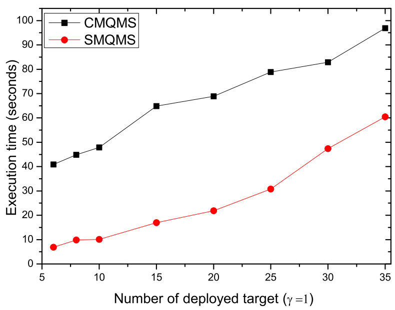


(a) Execution time vs. number of nodes



(b) Execution time vs. number of targets

Fig. 4. Impacts of execution time with varying number of (a) nodes and (b) targets for CMQMS and SMQMS system.

Typically, in wireless sensor network, the nodes are deployed with high density so as to schedule those alternately to extent the network lifetime [1], [27]. Furthermore, since every node in SMQMS works either as CH or a member node and given that the CMQMS system ensures the required coverage quality of all targets in the network, there is no reason that the SMQMS system suffers from insufficiency of sensor nodes to cover targets. Thus, the first condition (a) does not hold true.

Similarly, the second condition (b) cannot be held for SMQMS system since we consider all targets are covered by each and every member nodes of a CH $k \in \Upsilon$ (using Eq. 13). Moreover, the constraint (17) ensures that, all targets are covered by their required qualities. Therefore, our initial assumption contradicts with the achievable properties of SMQMS system. ■

Now, like CMQMS, the SMQMS system also becomes intractable one for increasing number of nodes, targets and monitoring area. We simulate the objective function of CMQMS and SMQMS systems in NEOS Optimization server (2x Intel Xeon E5-2698 @ 2.3GHz CPU and 92GB RAM) for given 20 snapshots of the network environment, and the results are shown in Fig. 4. The results reveal that, on an average, several seconds are required to execute the CMQMS and SMQMS systems for around $60 \sim 110$ number of nodes and $5 \sim 35$ targets. Also, as the node size in the network upsurges, it is difficult to find the results in polynomial time rather it requires exponentially high execution time (Fig. 4(a)). The reason is that, both the systems, calculate the number of subsets of the directions of nodes which increases as a power of nodes. However, since each CH distributedly selects the active nodes in the network, the SMQMS system has the ability to show better performance than the CMQMS system for larger number of nodes. The same is true for increasing number of targets (Fig. 4(b)). Nevertheless, it is quite challenging to provide results in polynomial time using SMQMS system for some real-time applications as sensors have very limited processing power and memory (nearly $5 \sim 8$ MHz and $2 \sim 108$ KB [41]). This challenge has motivated us to design a distributed greedy system to cover the targets.

C. Distributed Greedy MQMS-DSN System

In this section, we design a distributed greedy system, GMQMS-DSN for clustered networks. The GMQMS-DSN greedily maximizes either the network lifetime or sensing quality, implemented by two algorithms- (a) First-fit lifetime maximization (GMQMS-L, $\gamma = 1$) and (b) First-fit quality maximization (GMQMS-Q, $\gamma = 0$).

At first, each CH k finds a target set $\mathcal{M}_k$ using Eq. (13) by exchanging the nodes' and targets' information with neighbor CHs $l \in \Gamma_k$. The target set $\mathcal{M}_k$ constitutes three different types of targets in terms of coverage status, defined as follows,

$$\mathcal{M}_k = \mathcal{M}_k^F \cup \mathcal{M}_k^P \cup \mathcal{M}_k^U \tag{20}$$

where, $\mathcal{M}_k^F$ is the set of targets having coverage requirements fulfilled, $\mathcal{M}_k^P$ is the set of targets partially covered and $\mathcal{M}_k^U$ is the set of uncovered targets. The CH k also updates direction set Ψ_k as follows.

$$\Psi_k \leftarrow \Psi \backslash < i, \omega >, \quad E_r(i) < E_{th}, \ \forall i \in \mathcal{N}_k \tag{21}$$

where, $E_r(i)$ is the residual energy value of node i and E_{th} is the energy threshold, updated using Eq. (12). What follows next, is the detail description of the two strategies.

1) First-fit lifetime maximization (GMQMS-L): The key philosophy of designing GMQMS-L is to activate as minimum number of sensor nodes as possible to ensure required sensing coverage qualities of all targets in the networks. Each CH $k \in \Upsilon$ calculates a metric $\mathcal{L}_{i,\omega}$ for each sector $< i, \omega > \in \Psi_k$, as follows,

$$\mathcal{L}_{i,\omega} = w_1 \frac{|\tau_{i,\omega}|}{|\mathcal{M}_k^P \cup \mathcal{M}_k^U|} + w_2 \frac{\sum_{m \in (\mathcal{M}_{i,\omega} \backslash \tau_{i,\omega})} \sigma_{i,\omega}(m)}{\sum_{m \in (\mathcal{M}_k^P \cup \mathcal{M}_k^U) \backslash \tau_{i,\omega}} \varrho(m)} + w_3 \frac{E_r(i)}{E_o(i)}, \tag{22}$$

where, $\tau_{i,\omega} \subseteq (\mathcal{M}_{i,\omega} \cap (\mathcal{M}_k^P \cup \mathcal{M}_k^U))$ s.t. $\sigma_{i,\omega}(m) \geq \varrho(m)$, $\forall m \in (\tau_{i,\omega} \cap \mathcal{M}_k^U)$ or $\sigma_{i,\omega}(m) \geq (\varrho(m) - \sigma(m))$, $\forall m \in (\tau_{i,\omega} \cap \mathcal{M}_k^P)$. In other words, $\tau_{i,\omega}$ is the set of uncovered and partially covered targets whose remaining required coverage quality can be fulfilled by the sector $< i, \omega >$.

Note that, the computation of the metric $\mathcal{L}_{i,\omega}$ in Eq. (22) is done by weighted linear combination of three sub-metrics: the number of targets ($|\tau_{i,\omega}|$) whose requirements can be fulfilled, the contribution of the sector to cover more uncovered targets ($\sigma(m) < \varrho(m)$) and the residual energy of the sensors ($E_r(i)$)). Now, the CH k greedily activates a sensing sector $< i, \omega >$ that has maximum $\mathcal{L}_{i,\omega}$ value. The activation process of sensing sectors has been summarized in Algorithm. 2. One sector can be activated in only one direction at a time (line 9 of Algorithm. 2). After activating a sensor device, the value of $\sigma_{i,\omega}(m)$ and $\sigma(m)$ are updated $\forall m \in \mathcal{M}_{i,\omega}$; subsequently, the target sets $\mathcal{M}_k^F$, $\mathcal{M}_k^P$ and $\mathcal{M}_k^U$ are also updated (lines 11 $\sim$

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15). The CH k continues the above process until the required coverage qualities for all targets in the network are achieved or there is no other sensing sectors that can be activated (line 18).

Algorithm 2 First-fit lifetime maximization algorithm at each CH $k \in \Upsilon$

INPUT: $\Psi_k, \mathcal{M}_k, \mathcal{N}_k, \varrho(m), \sigma(m)$
OUTPUT: The set of nodes with active sensing sectors, ψ'_k

1. Update $\mathcal{M}_k$, Ψ_k using Eq. (13) and Eq. (21) respectively
2. $\Psi'_k \leftarrow \Psi_k$
3. $\mathcal{M}_k^F \leftarrow \phi,\ \mathcal{M}_k^P \leftarrow \phi,\ \mathcal{M}_k^U \leftarrow \mathcal{M}_k$
4. $\sigma(m) \leftarrow 0,\ m \in M_k$
5. **while** (1) **do**
6.   **Calculate** $\mathcal{L}_{i,\omega},\ \forall <i,\omega> \in \Psi_k$ using Eq. (22)
7.   **Find** $<i,\omega>$ having the maximum $\mathcal{L}_{i,\omega}$,
8. $\psi'_k \leftarrow <i,\omega>$
9. $\Psi'_k \leftarrow \Psi'_k \setminus <i,\omega>,\ \forall \omega \in \Omega,$
10.   **for all** $m \in \mathcal{M}_{i,\omega}$ **do**
11.   **Calculate** the quality $\sigma_{i,\omega}(m)$, $\sigma(m)$, using Eq. (2) and Eq. (3) for $<i,\omega>$
12.   **if** $(\sigma(m) \geq \varrho(m))$ **then**
13. $\mathcal{M}_k^F \leftarrow m,\ \mathcal{M}_k^U \leftarrow \mathcal{M}_k^U \setminus m,\ \mathcal{M}_k^P \leftarrow \mathcal{M}_k^P \setminus m$
14.   **else**
15. $\mathcal{M}_k^P \leftarrow m,\ \mathcal{M}_k^U \leftarrow \mathcal{M}_k^U \setminus m$
16.   **end if**
17.   **end for**
18.   **if** $((\mathcal{M}_k^U == \phi$ **AND** $\mathcal{M}_k^P == \phi)$ **OR** $\Psi'_k == \phi)$ **then**
19.   EXIT
20.   **end if**
21. **end while**

---

2) First-fit quality maximization (GMQMS-Q): In this section, we present our strategy for enhancing quality of sensing coverage for all targets in the network. The key philosophy is to greedily activate a sensing sector that gives the highest coverage quality to the targets. Thus, each CH $k \in \Upsilon$ calculates a quality metric $\mathcal{Q}_{i,\omega}$ for all sector $<i,\omega> \in \Psi_k$ as follows,

$$\mathcal{Q}_{i,\omega} = w\frac{\sum\limits_{m\in\tau_{i,\omega}}\sigma_{i,\omega}(m)}{\sum\limits_{m\in(\mathcal{M}_k^P\cup\mathcal{M}_k^U)}\varrho(m)} + (1-w)\frac{\sum\limits_{m\in(\mathcal{M}_{i,\omega}\setminus\tau_{i,\omega})}\sigma_{i,\omega}(m)}{\sum\limits_{m\in(\mathcal{M}_k^P\cup\mathcal{M}_k^U)\setminus\tau_{i,\omega}}\varrho(m)}, \tag{23}$$

where, w is a weight parameter. Similar to Algorithm. 2, the steps of first-fit-quality maximization has been summarized in Algorithm 3.

The complexity of the two algorithms 2 and 3 can be calculated as follows: lines 5 to 21 are enclosed in a while loop that can run $O(|\Psi_k|)$ times. Inside the while loop, there is a for loop that has complexity $O(|\mathcal{M}_k|)$ (line 10 to 17)). Therefore, the overall complexity of the algorithms 2 and 3 is $O(|\mathcal{M}_k| \times |\Psi_k|)$.

Algorithm 3 First-fit quality maximization algorithm at each CH $k \in \Upsilon$

INPUT: $\Psi_k, \mathcal{M}_k, \mathcal{N}_k, \varrho(m), \sigma(m)$
OUTPUT: The set of nodes with active sectors, ψ'_k

1. **Update** $\mathcal{M}_k$, Ψ_k using Eq. (13) and Eq. (21), respectively
2. $\Psi'_k \leftarrow \Psi_k$
3. $\mathcal{M}_k^F \leftarrow \phi,\ \mathcal{M}_k^P \leftarrow \phi,\ \mathcal{M}_k^U \leftarrow \mathcal{M}_k$
4. $\sigma(m) \leftarrow 0,\ m \in M_k$
5. **while** (1) **do**
6.   **Calculate** $\mathcal{Q}_{i,\omega},\ \forall <i,\omega> \in \Psi_k$ using Eq. (23)
7.   **Find** $<i,\omega>$ having the maximum $\mathcal{Q}_{i,\omega}$,
8. $\psi'_k \leftarrow <i,\omega>$
9. $\Psi'_k \leftarrow \Psi'_k \setminus <i,\omega>,\ \forall \omega \in \Omega,$
10.   **for all** $m \in \mathcal{M}_{i,\omega}$ **do**
11.   **Calculate** the quality $\sigma_{i,\omega}(m)$, $\sigma(m)$, using Eq. (2) and Eq. (3) for $<i,\omega>$
12.   **if** $(\sigma(m) \geq \varrho(m))$ **then**
13. $\mathcal{M}_k^F \leftarrow m,\ \mathcal{M}_k^U \leftarrow \mathcal{M}_k^U \setminus m, \mathcal{M}_k^P \leftarrow \mathcal{M}_k^P \setminus m$
14.   **else**
15. $\mathcal{M}_k^P \leftarrow m,\ \mathcal{M}_k^U \leftarrow \mathcal{M}_k^U \setminus m$
16.   **end if**
17.   **end for**
18.   **if** $((\mathcal{M}_k^U == \phi$ **AND** $\mathcal{M}_k^P == \phi)$ **OR** $\Psi'_k == \phi)$ **then**
19.   EXIT
20.   **end if**
21. **end while**

D. Determination of Weighting Parameters

In this section, we discuss on values chosen for factor values ζ, w_1, w_2, w_3 and w that are used in Eq. (12), Eq. (22) and Eq. (23).

Introducing ζ in Eq. (12), helps more nodes to participate in activation process, upsurging network lifetime. Over the course of time, the residual energy of a node gradually decreases and keeping the energy threshold (E_{th}) at a fixed point, restraints to form new active sets. Determining the value of ζ depends on dynamic nature of the network parameters and it leads us to a new research dimension. In this work, we have done extensive simulations for choosing a suitable value for ζ and set ζ = $\frac{1}{2}$ for all experiments .

Similarly, the optimal values of weight factors w, w_1, w_2 and w_3 used in Eq. (22) and Eq. (23) are corresponding to complex multivariable functions, highly depend on the network size and shape, node density, initial node energy, etc. In the design of GMQMS system, we have gone simulation based approach for setting the values of these parameters which is one of our key limitations. We run our simulations by setting the values as $w_1 = 0.42$, $w_2 = 0.32$, $w_3 = 0.26$ and $w = 0.55$.

V. Performance Evaluation

In this section, we present comparative performances of the proposed MQMS-DSN systems and maximal network lifetime scheduling (MNLS) system [10], a mixed integer programming problem.

A. Simulation Environment

The experiments have been carried out in a discrete event network simulator ns-3 [19]. Sensors and targets are deployed

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TABLE II
NETWORK SIMULATION PARAMETERS

Parameters	**Value**
Area of deployment	$500m \times 500m$
Type of deployment	Random (Uniform)
Sensor nodes deployed	$100 \sim 400$
Number of targets	$15 \sim 50$
Sensing sectors	$2 \sim 6$
Field of view	$60^o \sim 180^o$
Sensing range	$30 \sim 80m$
Transmission range	$60 \sim 160m$
Node energy (initial)	6 J
E_{th}	1 J
Network bandwidth	512 Kbps
Data packet size	512 bytes
ACK size	14 bytes
Control packet size	16 bytes
Physical layer model	YansWifi Model
Simulation time	1000 Seconds

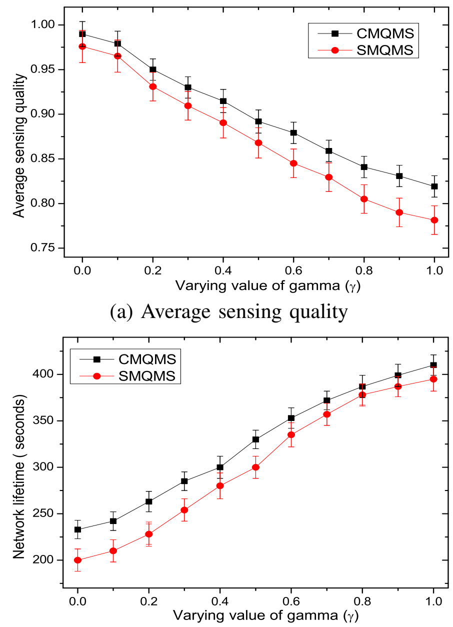
in a region of $500 \times 500m^2$ with uniform random distribution. For different experiments, we have varied the number of sensors from 100 to 400 and targets from 15 to 40. YansWifiPhy model is used for adjusting the channel properties like the propagation delay model, data rate, delay loss model and other channel properties. For the cluster-based solutions (SMQMS and GMQMS), we use a clustering algorithm for directional sensor network, described in [2]. The simulation parameters are shown in Table II.

The required coverage quality, $\varrho(m)$ for a target $m \in \mathcal{M}$ is randomly chosen from the range [0.7,1]. The value of λ, β are set as 0.5 and 0.5 following the discussion in [18]. In measuring performances of proposed CMQMS and SMQMS, the value of γ is set to 0 for maximizing coverage quality and to 1 for maximizing network lifetime. The clusters are formed using TCDC algorithm [2] with parameters specified in section 6.1 and 6.1 of [2]. All nodes in the network use the same transmission range in all transmission attempts irrespective of location of their destination nodes. Each simulation was run for 1000 seconds and the graph data points are plotted for the average of the results from 30 simulation runs.

B. Performance Metrics

- *Average sensing quality:* It is measured as the average of sensing qualities given to all targets by a system. Higher value of this metric indicates better capability of the system to provide quality coverage to the targets.
- *Network lifetime:* It is calculated as the summation of the lifetime of all active sets ([10], [42]) in the network.
- *Percentage of active sensor nodes:* It is defined as the ratio of number of sensor nodes activated by a system to the total number of sensor nodes in the network.
- *Standard deviation of residual energy:* It represents how well the energy consumption load of the network nodes is distributed and is calculated as follows,

$$\varpi = \sqrt{\frac{1}{|\mathcal{N}|}\sum_{i=1}^{|\mathcal{N}|}(E_r(i) - \nu)^2}, \tag{24}$$



(a) Average sensing quality

(b) Network lifetime

Fig. 5. Impacts of control parameter γ on the performances of CMQMS and SMQMS systems

where, $E_r(i)$ is the node i's residual energy and the mean residual energy of all nodes is indicated by ν. The lower value of ϖ represents better energy-load balance in the network.

C. Simulation Results

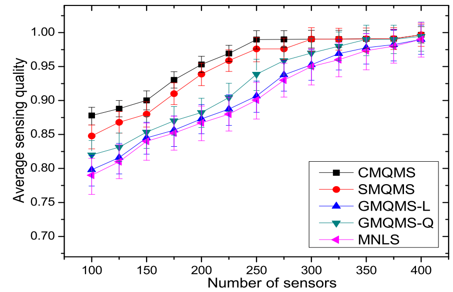
In this section, we discuss on the results of performance evaluations for varying values of control parameter γ, number of sensor nodes, number of targets, sensing ranges and number of sensing sectors.

1) Impacts of varying values of control parameter, γ: We have varied the value of γ and assessed the performances on network lifetime and average sensing quality achieved by CMQMS and SMQMS systems. The value of γ controls the level of importance an application requires on sensing quality and network lifetime. For this experiment, the area, number of targets, sensor nodes, sensing sectors and sensing radius are kept constant at 500m $\times$ 500m, 25, 250, 4 and 50m respectively. From the graphs Fig. 5(a) and Fig. 5(b) it is clear that, sensing quality and network lifetime are inversely related to each other for increasing values of control parameter γ. Both CMQMS and SMQMS maximize the network lifetime when $\gamma = 1$ while keeping the required sensing qualities for all targets in the network. Similarly the overall sensing quality for all targets are maximized when $\gamma = 0$ while ensuring balanced energy consumption across all sensor nodes in the networks. However, other values of γ facilitate the systems to make a trade off between lifetime and quality. Thus the values of γ is set by the system administrator following the requirements of intended application.

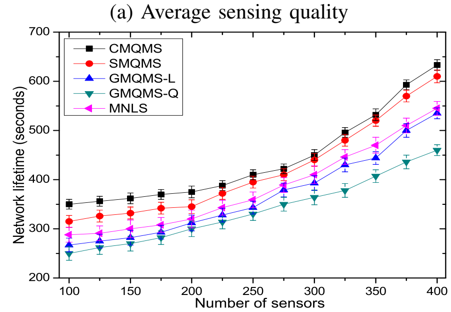
2) Impacts of varying number of nodes: We have varied the number of sensor nodes in the network to analyze the scalability of our proposed MQMS-DSN systems. For this experiment, the number of sectors, sensing radius and number of targets are kept constant at 4, 50m, 25, respectively. From the graphs of Fig. 6(a), we observe that, our proposed MQMS–DSN systems offer better average sensing quality than the state-of-the-art-work MNLS [10] for increasing number of nodes. Compared with our MQMS-DSN systems, the MNLS achieves poor coverage quality ratio since its primary objective is to enhance the network lifetime. We have noticed that, the proposed CMQMS system achieves full sensing coverage with less number of nodes compared to all other systems. The results are as expected theoretically , because CMQMS has the ability to pick the optimal solution from all the combinations to enhance the coverage quality (for $\gamma = 0$). However, the greedy solution GMQMS-Q offers improved performance compared to that of MNLS and GMQMS-L as it is designed to enhance the quality rather than lifetime. The most interesting outcome of this experiment is that the performance gap in between the studied systems are decreased with the increasing node densities. The suboptimal and greedy solution reach the performances of the optimal solution when the number of nodes in the network crosses 300. The reason behind achieving these result is the lack of information in the current status of the network at the central node.

For increasing the node density, the network lifetime upsurges in all the studied systems as coherent with the theory. However, from the graphs of Fig. 6(b), we observe that, the CMQMS performs better compared to the other systems for different node densities. Nevertheless, MNLS achieves quite inferior result than CMQMS and SMQMS. Although SMQMS is a cluster based-distributed solution, the energy-aware selection of nodes, dynamic updating of energy threshold value and instantaneous decision making help the SMQMS system to provide better lifetime than the MNLS. On the contrary, the GMQMS-L system has low performance than the CMQMS and SMQMS as the former greedily chooses local optimal nodes and thus often fails to achieve global optimal results.

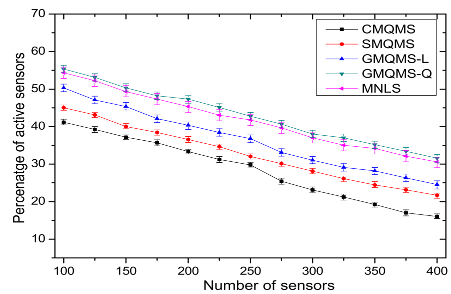
We also plot the performance results of percentage of active sensor nodes for different systems varying the node densities. The graphs of Fig. 6(c) reveal that the optimal and suboptimal formulation of the MQMS-DSN system i.e., CMQMS and SMQMS achieve better outcomes compare to all others. This happens due to the strategy of the MILP formulation of the two, that aims to minimize the number of sensor nodes. However, MNLS achieves poor performance than the GMQMS-L as it does not consider to minimize the number of sensor nodes.



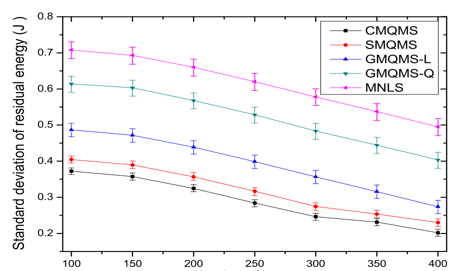
(a) Average sensing quality



(b) Network lifetime



(c) Percentage of active sensor nodes

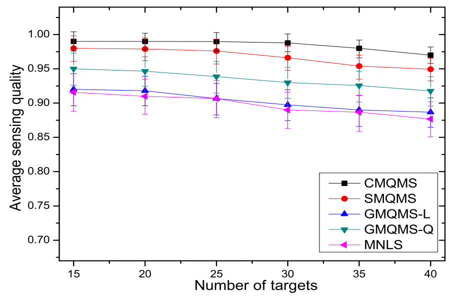


(d) Standard deviation of residual energy

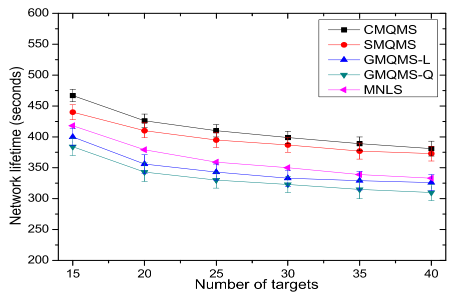
Fig. 6. Impacts of varying sensor nodes (area = 500m $\times$ 500m, sensing radius = 50m, target = 25, sensing sector = 4)

The standard deviation of residual energy values for all nodes in the studied systems are plotted in Fig. 6(d). We observe that, our MQMS-DSN systems outperform than the state-of-the-art-work MNLS. The results are achieved due to the minimization of number of sensor nodes, residual energy-aware selection of nodes, updating threshold value dynamically and instantaneous decision making on selecting active nodes.

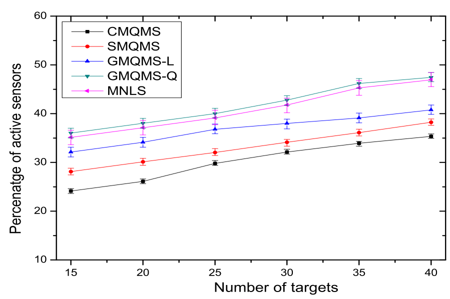
3) Impacts of varying number of targets: We gradually increase the number of targets in the network and study its impact on the performances of the studied systems. Employing the proposed algorithms for various targets would shed light to the robustness of the proposed MQMS-DSN systems. The number of sectors, sensing radius and number of nodes are fixed at 4, 50m, 250 for this experiment. The graphs in Fig. 7(a), portray the relationship between the number of average sensing quality and number of targets of the evaluated systems. For increasing number of targets, the average sensing quality remains almost same or decreasing very slightly for all the systems which is sensible as average value is taken. However, the proposed MQMS systems have the ability to achieve better quality with respect to MNLS [10] for varying number of targets, where as the performance of GMQMS-L is close to MNLS. The objectives of MNLS and GMQMS-L



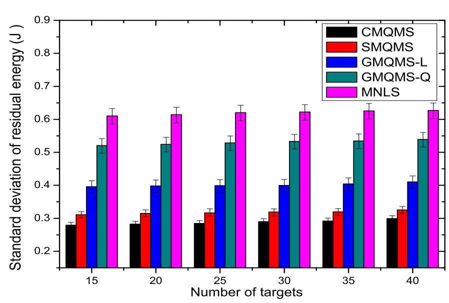
(a) Average sensing quality



(b) Network lifetime



(c) Percentage of active sensor nodes



(d) Standard deviation of residual energy

Fig. 7. Impacts of varying targets (area = 500m × 500m, sensing radius = 50m, number of nodes = 250, sensing sector = 4)

are to enhance network lifetime rather quality, which restricts those to achieve high sensing quality compare to others.

For upsurging the number of targets, the network lifetime lessens for all the systems that are consistent with the theoretical results as shown in Fig. 6(b). We also notice an interesting phenomenon, initially the decreasing rate of lifetime is very high; however, after certain number of targets (here it is 25) the rate declines slowly. The reason is that, as we are enhancing the targets maintaining fixed number of sensor nodes, it increases the chance to cover more number of targets by the active nodes.

From the graphs in Fig. 7(c), it is clear that the percentage of active nodes increases for all the systems with the growing number of targets. The reason is straight forward, as increasing the number of targets demands more nodes to be activated, resulting increased number of active nodes. Nevertheless, our proposed CMQMS, SMQMS and GMQMS-L show improved results for their working approach to minimize the number of sensor nodes over MNLS and GMQMS-Q ($\gamma = 1$).

For varying number of targets, the standard deviation for all the systems are shown in Fig. 7(d). The experimental outcomes reveal that, the proposed MQMS-DSN systems have better capacity to balance the energy consumption compare to MNLS for its working strategy to select the active nodes considering residual energy, dynamically updating energy threshold value and instantaneous decision making of active nodes.

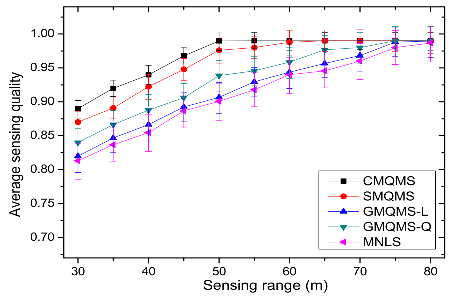
4) Impacts of varying sensing ranges: We have also studied the comparative performances for varying sensing ranges. For this experiment, we have deployed 250 number of nodes with 25 targets, keeping the number of sensing sector fixed at 4. Increasing the sensing range enhances the chance to cover more targets by the nodes that results increasing the average sensing quality and the network lifetime. For the same reason, the percentage of active nodes also decreases. The other reason for achieving better results by the proposed MQMS-DSN systems, as depicted in Fig. 8, are already stated before.

5) Impacts of number of sectors: In this experiment, we evaluate the impacts of the number of sensing sectors (ranging from 2 to 6) of the sensor nodes on the performances of the studied systems. The number of targets, sensor nodes and sensing range are fixed at 25, 250, 50m, respectively. The graphs in Fig. 9(a) state that, the average sensing quality decreases with increasing number of sectors in all the studied systems. High number of sectors means lower size of FOV that limits to cover more targets. The graphs also reveal that despite of increasing number of sectors, MQMS-DSN systems achieve better results than the MNLS. As shown in Fig. 9(b), the network lifetime is gradually increased with the increasing number of sensing sectors for all the studied systems. This happens as, sensors with small FOV size consume low energy. For increasing number of sectors, percentage of active sensor nodes increases, as depicted in Fig. 9(c). However, less number of nodes remain active in CMQMS, SMQMS and GMQMS-L compared to those of MNLS and GMQMS-Q.

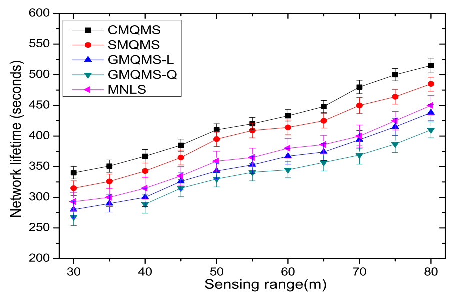
The graphs in Fig. 9(d) indicate that, for all the systems, the standard deviation of residual energy level lessen gradually for growing number of sectors. The proposed MQMS-DSN systems achieve improved performance than other. As expected, relatively large value of sectors also enhances the choices for the central controller to select nodes to keep in active or in sleep state that consequently preserves the energy.

VI. Conclusion

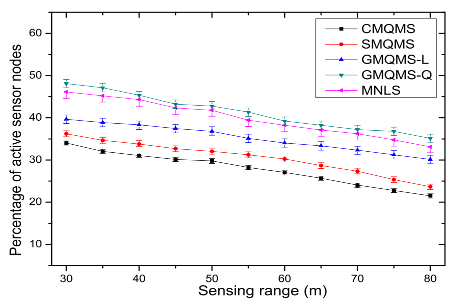
This paper has addressed the joint problem of maximizing the sensing coverage quality and the network lifetime for covering heterogeneous targets in Smart City applications. To the best of our knowledge, this work first develops a general framework that studies boundary analysis, both for the coverage quality and network lifetime, in addition to making an efficient tradeoff between the two. The results of



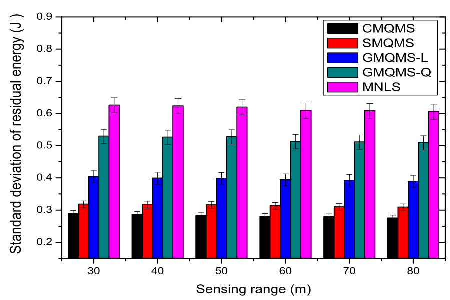
(a) Average sensing quality



(b) Network lifetime

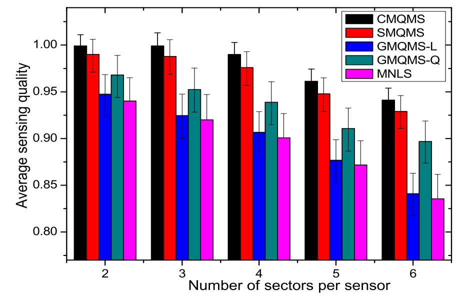


(c) Percentage of active sensor nodes

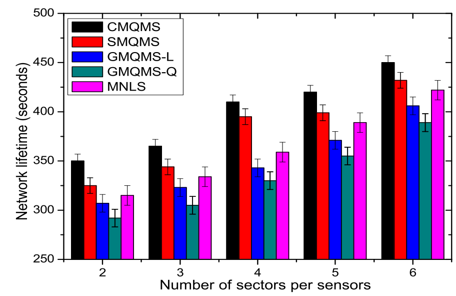


(d) Standard deviation of residual energy

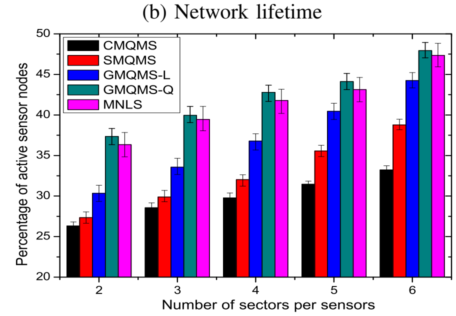
Fig. 8. Impacts of varying sensing ranges (area = 500m × 500m, number of targets = 25, number of nodes = 250, sensing sector = 4)



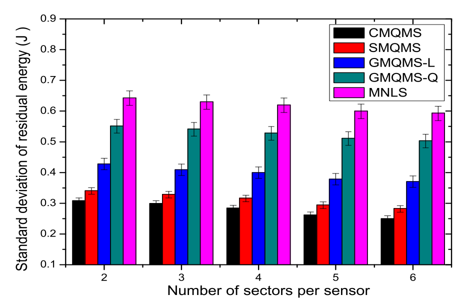
(a) Average sensing quality



(b) Network lifetime



(c) Percentage of active sensor nodes



(d) Standard deviation of residual energy

Fig. 9. Impacts of varying sensing sectors (area = 500m × 500m, number of targets = 25, number of nodes = 250, sensing radius = 50m)

the experiments reveal that, rather than executing precomputed coverage decisions, instantaneous situation-aware dynamic coverage plans are more effective to enhance the network performance. The outcome of this research also states that, the optimal coverage algorithms are not practically usable for large Smart City application networks with enormous sensor nodes and targets; in such situations, greedy coverage algorithms with probabilistic sensing quality measurements provide with performances near to that of optimal solution.

Although our proposed strategy achieves better sensing coverage quality and network lifetime, further theoretical and experimental extensions are possible. In future, we plan to investigate the problem of developing a suitable clustering algorithm that works better with the proposed MQMS-DSN systems.

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