DESIGN OF ALGORITHMS TO ASSOCIATE SENSOR NODES TO FUSION CENTERS USING QUANTIZED MEASUREMENTS

DESIGN OF ALGORITHMS TO ASSOCIATE SENSOR NODES TO FUSION CENTERS USING QUANTIZED MEASUREMENTS

By SAROJINI VUDUMU, M.E

A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy

McMaster University

DOCTOR OF PHILOSOPHY (2023)

Hamilton, Ontario, Canada (Department of Electrical and Computer Engineering)

TITLE:	Design of Algorithms to Associate Sensor Nodes to Fusion Centers Using Quantized Measurements
AUTHOR:	Sarojini Vudumu ME (Computer Science and Engineering), Indian Institute of Science, Bangalore, India
SUPERVISOR:	Dr. Thiagalingam Kirubarajan, Dr. Ratnasingham Tharmarasa
NUMBER OF PAGES:	xv, 154

Abstract

Wireless sensor networks (WSNs) typically consist of a significant number of inexpensive sensor nodes, each of which is powered by a battery or another finite energy source that is difficult to replace because of the environment they are in or the cost of doing so. The applications of WSNs include military surveillance, disaster management, target tracking and monitoring environmental conditions. In order to increase the lifespan of WSNs, energy-efficient sensing and communication approaches for sensor nodes are essential. Recently, there has been an increase in interest in using unmanned aerial vehicles (UAVs) as portable data collectors for ground sensor nodes in WSN. Several approaches to solving effective communication between sensor nodes and the fusion center have been investigated in this thesis. Because processing, sensing range, transmission bandwidth, and energy consumption are always limited, it is beneficial not to use all the information provided at each sensor node in order to prolong its life span and reduce communication costs. In order to address this problem, first, efficient measurement quantization techniques are proposed using a single fusion center and multiple sensors. The dynamic bit distribution is done among all the sensors and within the measurement elements. The problem is then expanded to include multiple fusion centers, and a novel algorithm is proposed to associate sensors to fusion centers. The bandwidth distribution for targets which are being monitored by several sensors is addressed. Additionally, how to use the situation in which the sensors are in the coverage radius of multiple fusion centers in order to share the targets between them is discussed. Finally, performance bounded data collection algorithms are proposed where the necessary accuracy for each target is specified. In order to determine the minimum number of data collectors needed and their initial placement, an algorithm is proposed. When there are fewer fixed data collectors than there are regions to collect the data from, a coverage path planning method is developed. Since the optimal solution requires an enormous computational requirement and not realistic for real-time online implementation, approximate algorithms are proposed for multi-objective integer optimization problems. In order to assess each suggested algorithm's effectiveness, many simulated scenarios are used together with baselines and simple existing methods.

To my Beloved Mother

For passing on her resilient faith

Acknowledgements

First and foremost, I am grateful to the LORD Almighty and Redeemer for His amazing grace and abundant mercy and for holding me fast in all difficult circumstances.

I would like to express my special gratitude to my supervisor, Dr. Kiruba, for enabling me to realize my wish and giving me the precious opportunity to learn and work under his supervision. I am truly amazed at your immense knowledge and extensive experience. You always inspire me to work hard with passion. It is indeed my privilege to work with you and know you. I hope to cultivate your humble attitude. I am forever grateful to you.

It is a wonderful experience to work with two supervisors. I am very thankful to my co-supervisor, Dr. Thamas, for his great patience, enthusiasm, encouragement, and many brilliant, detailed discussions, which have greatly benefited me in completing this study. You are always available and supportive. You helped me see the practicality of the research work and to think critically. Your dedication, friendly supervision, and helpful nature are really inspiring. Your guidance has greatly enriched my work. You have been instrumental in the completion of my study.

I would like to express my sincere thanks and gratitude to my committee members, Dr. Timothy Field and Dr. Aleksandar Jeremic, for their insightful comments and helpful suggestions during all my committee meetings. Thank you, Professor Dr.

Kumaradevan Punithakumar, for your invaluable time and insights in reviewing my thesis.

Thank you, Michael Bradford, for the opportunity to work with you during my Co-op, and I have learned a lot under your mentorship, both in technical and personal skills, at L3 Harris Wescam. You always motivated me to think outside the box and make complex things simpler. I can say you are an exemplary manager.

Thank you very much, Cheryl Gies, Tracey Coop, Mary Anne, and Christine Rich, for keeping me on track.

Sincere thanks to all my good friends, Abhijit, David, Josh, Prakhar, Prabhanjan, Anbang, Dipayan, Aranee, Nikhil, Honghao, Sujana, Tracy, Danielle, Sheila, Denise, and Esther. They make my life a little bit easier and more fun. I am so glad our paths crossed.

Thanks to my blessed family, Amma, Akka1, Akka2, Akka3, Raju, Chinji, Jeremy, KC, and all extended family members for their love and unceasing support through thick and thin. I am indebted to them for making this possible.

To all who are not mentioned here but helped me to complete this study one way or another, thank you so much. I deeply appreciate your help.

Table of Contents

List of Figures

List of Tables

Abbreviations

Abbreviations

WSN	Wireless Sensor Network
UAV	Unmanned Aerial Vehicle
FC	Fusion Center
PCRLB	Posterior Cramér-Rao Lower Bound
RMSE	Root Mean Squared Error
DC	Data Collector
GNN	Global Nearest Neighbor
GA	Genetic Algorithm
ROI	Region Of Interest
DP	Dynamic Programming
LOS	Line-Of-Sight

IoT	Internet of Things
FIM	Fisher Information Matrix
SROI	Shared Region Of Interest

Declaration of Academic Achievement

I, Sarojini Vudumu, declare that this thesis, titled "Design of Algorithms to Associate Sensor Nodes to Fusion Centers Using Quantized Measurements" and the work presented in it are my own. Additionally, I declare that I have acknowledged the work of others, which is used for discussion and analysis, by providing detailed references to said work. Coauthors are identified and credited clearly.

Chapter 1

Introduction

1.1 A Review of Measurement Quantization and Data Collection

Multi-target tracking problems often require covering extremely large areas, and many sensors are densely deployed to cover the region of interest (ROI). This results in new challenges when resources like power, bandwidth, and energy are limited. Utilizing all the sensors in the ROI, including the uninformative ones that rarely help the tracking of the target at hand but use limited available resources, is ineffective in these circumstances[11]. Wireless sensor networks (WSN) provide diverse opportunities to detect and interact with the physical world around us. They enable us to gather data that was until now difficult, expensive, or even impossible to collect. A particularly challenging problem in wireless sensor network applications is developing an energy-efficient tracking approach that balances the limited energy resources with the tracking performance requirements. Despite the many promising benefits, there are many new challenges to address to have an efficient association of sensors to fusion centers (FC) and the amount of data for each target to be communicated by the sensors to the fusion centers. This calls for more effective resource management systems. It is acknowledged that providing direct measurements rather than estimates makes optimal data fusion possible. Recent research has demonstrated the competitiveness of such an approach in terms of bandwidth. This thesis investigates the bandwidth allocation in terms of the number of bits per measurement through intelligent quantization and the assignment of targets to fusion centers. Figure 1.1, depicts the scenario where the sensor nodes have limited energy and the fusion center collects the measurements from these sensor nodes to obtain an overall view of the tracking region with multiple targets. As a result, communication required expensive sensor node energy usage. Sensor data is transmitted through channels with a limited amount of bandwidth in real systems. Therefore, it is crucial to think about problems with quantized data transfer from the sensors to the fusion center and ultimately the fusion of such quantized data. Redundancy is created when there is a dense deployment of sensor nodes because numerous sensors are simultaneously producing information about the target. The question of how much data should be gathered from each sensor node to improve tracking accuracy then emerges. The motivation behind this thesis is to improve and extend the existing data collection methods to handle different scenarios that arise while collecting the data for multitarget tracking. This thesis is structured as a sandwich thesis with three separate publications that address three interrelated issues associated with data collection in WSNs. Applications such as surveillance, traffic monitoring, and rescue operations are taken into consideration.

Due to the rapid increase in the number of sensors in the surveillance region, in

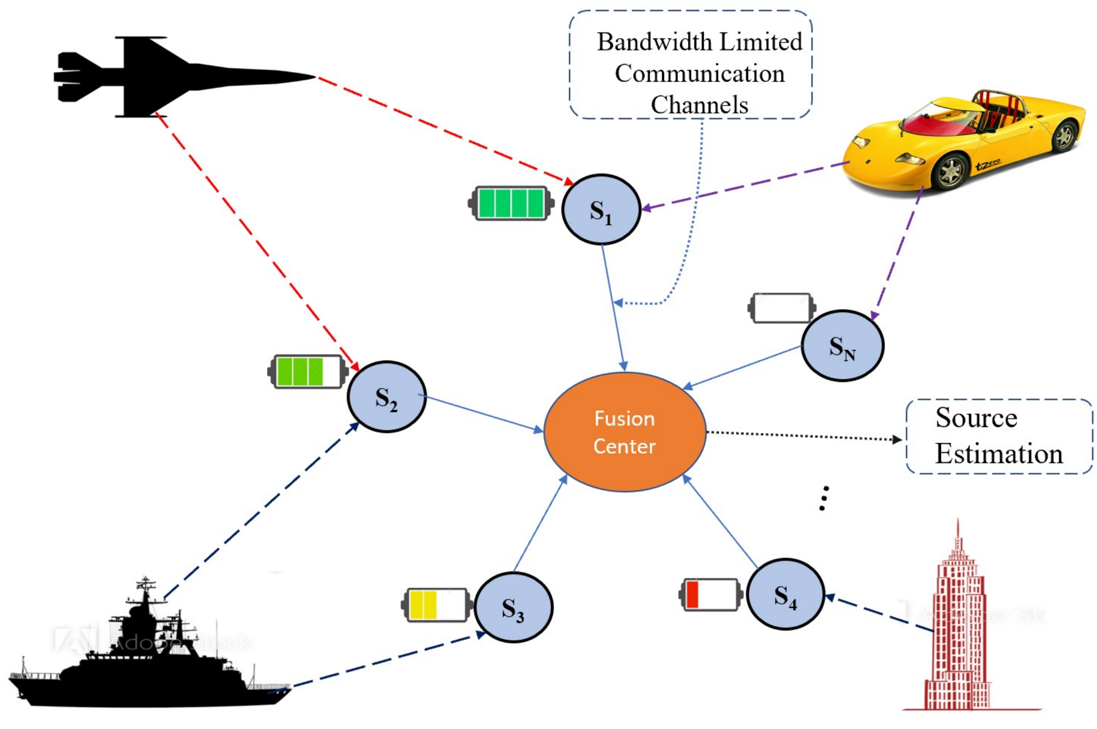


Figure 1.1: Multi-Target Tracking with Quantized Measurements

Multi-Sensor, Multi-Targets scenarios, raw sensor measurements are typically quantized before being sent to the information processing center (fusion center) due to the limited communication bandwidth. The amount of bandwidth required to communicate all the measurements from all the sensors is competitive. Selecting a smaller number of quantized sensor measurements may nevertheless produce data of the necessary quality in a surveillance system such as a combat scenario, where dense sensor deployment may result in redundancy in coverage. In Chapter 2, we pose and solve the topic of how to distribute the bits when a sensor has several targets and each target's measurement has more than one element, along with how to leverage data from many sensors to initialize the tracks in the shared region more quickly. An intelligent and effective quantization for multi-target tracking by dynamically allocating the available bandwidth among all the targets is studied. The fusion center effectively distributes the available bandwidth among the targets at each time step in order to minimize the posterior Cramer-Rao lower bound on the mean squared error. To do this, the fusion center also takes into account the bandwidth at the sensor nodes.

Energy-efficient data collection in wireless sensor networks utilizing unmanned aerial vehicles as mobile data collectors is a key requirement in any network design to prolong the network's lifetime. Although UAVs, or drone cells, provide a quick deployment opportunity as aerial base stations, efficient data collection from different sensors becomes one of the key issues, especially in an energy and bandwidth-limited environment. In Chapter 3, we first highlight the situation where a sensor can be in the coverage region of more than one fusion center and the advantage of a sensor communicating with multiple fusion centers where the energy at the fusion centers and sensor nodes is limited. The issue of connecting the targets to fusion centers and the distribution of bandwidth to the targets are both addressed in our work. We formulate the problem as a multi-objective integer problem to get the best tracking performance as the main objective by efficiently using the available resources, which is achieved by minimizing the posterior Cramer-Rao lower bound for tracking in cluttered domains.

Wireless sensor networks have become an important solution for a wide range of ever-growing tracking applications. Many of the conventional WSN architectures consist of static sensor nodes that are densely deployed over a tracking region. The information from these stationary sensor nodes is gathered using data collectors (DC) such as an unmanned aerial vehicle. These data collectors are generally used as a central communication point for all wireless devices. The deployment of the data collectors and their maintenance are expensive endeavours. It is a very crucial step to decide the number of data collectors to deploy in a given tracking region. The next question we ask and address is: given the number of targets and their accuracy requirements, how many data collectors with limited capabilities and bandwidth restrictions are to be deployed, and how do we associate the sensor nodes with the data collectors such that the Mean Square Error performance goal is achieved with a minimal number of bit assignments? The first problem to handle is to compute the bit requirement for each target based on the given accuracy requirement. The second problem to address is to compute the number of data collectors required to cover all the sensors and achieve the desired performance limits. In Chapter 4, we propose a novel method to calculate the number of data collectors to deploy and to place them in an adaptive way as the load changes at each sensor node. Based on the sensor load, we model the initial placement strategy for data collectors. For the initial deployment of data collectors and their association with sensor nodes, we provide an approximate but suboptimal approach.

The rest of this thesis is divided into the following sections. In Section 1.2, a list of the publications upon which the subsequent chapters are based as well as a brief synopsis of the thesis contributions are provided. Each of the issues mentioned above is thoroughly covered in chapters 2 through 4. Every one of these chapters provides a full overview of the relevant issue, as well as information on the shortcomings of current approaches, suggested fixes, experiments to verify the suggested fixes, and associated discussions. Chapter 5 provides a conclusion.

1.2 Thesis Contributions

The following are the contributions of this thesis:

- The bit allocation problem is formulated as a multi-objective integer optimization problem that minimizes the PCRLB across all targets and complies with the bandwidth restrictions. In the creation of the dynamic bit allocation, bandwidth restrictions at the FC and each sensor node are taken into account (chapter 2).
- An approximate bit allocation algorithm is proposed that distributes bits across the components of the measurement vector as well as to each of the targets at the fusion center (chapter 2).
- A novel strategy is proposed for joint bandwidth allocation and assignment of targets to fusion centers for multi-target tracking in multiple distributed radar networks under cluttered background (chapter 3).

- For joint bandwidth allocation and target assignment, two approximate distribution algorithms are proposed. These algorithms deliver almost ideal outcomes in a shorter amount of time (chapter 3).

- An algorithm is proposed for generating initial values for the multi-objective integer optimization problem (chapter 3).

- The calculation of the minimum number of data collectors with restricted bandwidth and coverage area needed to cover all the sensors and obtain the specified accuracy results for each target (chapter 4).

- The formulation of a multi-objective optimization problem to describe the relationship between data collectors and sensor nodes, where each sensor is associated with just one data collector (chapter 4).

- The formulation of a coverage path planning problem for covering the regions with a predetermined number of data collectors (chapter 4).

Chapters 2, 3, and 4 of this thesis were all originally intended to be research papers. For convenience and to properly credit the co-authors, the full citation for each is provided below.

[66]. Sarojini Vudumu, Dr. Ratnasingham Tharmarasa, Dr. Thiagalingam Kirubarajan, and Dr. Anne-Claire Boury-Brisset. "Efficient quantization for multi-target tracking." *To be submitted to IEEE Transactions on Aerospace and Electronic Systems, July, 2023.*

[64]. Sarojini Vudumu, Dr. Ratnasingham Tharmarasa, Dr. Thiagalingam Kirubarajan. "Joint bandwidth allocation and assignment of targets to multi- ple fusion centers for distributed multi-target tracking." *To be submitted to IEEE Transactions on*

Aerospace and Electronic Systems, July, 2023.

[65]. Sarojini Vudumu, Dr. Ratnasingham Tharmarasa, Dr. Thiagalingam Kirubarajan. "Efficient performance bounded data gathering for distributed multi- target tracking." *To be submitted to IEEE Transactions on Aerospace and Electronic Systems, July, 2023.*

Chapter 2

Efficient Quantization for Multi-Target Tracking

2.1 Introduction

A distributed sensor network consists of numerous spatially distributed sensors, which are tiny, battery-powered devices with limited onboard energy. These networks can perform a wide range of applications, both for military and civil applications, ranging from battlefield surveillance environments, to disaster relief operations. The dense deployment of sensors in the network introduces redundancy in coverage. It is desirable not to use all the sensors to track a target at each time, since there always exist constraints on computation, sensing range, communication bandwidth, and energy consumption[8, 26, 16, 17, 15, 61]. Thus, a critical task is to distribute the resources among the sensors to optimize system performance under these constraints. In many networks, in order to reduce both energy and bandwidth requirements, measurement quantization is employed. When quantization is used, it plays a major role in determining the error performance of the network. Different from the difficulty of quantizing a signal for later reconstruction is the problem of quantizing observations to estimate a parameter, such as a target position or any other environmental field such as temperature, humidity, etc. Our goal is to estimate the target trajectory using quantized measurements rather than reassemble a signal. Several articles on tracking in sensor networks based on quantized sensor measurements are available. Using quantized data delivered across a noisy channel between sensors and a fusion center, the authors of [55] create a new framework for target tracking. The authors of [62] suggest an intelligent quantizer for measurement fusion that is based on delta-modulation. Each sensor's quantizer is created dynamically based on the most recent target state estimate supplied by the fusion center. A two-step optimization process was suggested for a single target in [56]. First, for every sensor, identify the optimal time-independent quantizers that correspond to all potential bandwidth distributions offline, and store them. As a next step, select the ideal bandwidth distribution using the quantizers found in step one. Each sensor quantizes the measurements before sending them to the Fusion Center (FC)[9, 58, 10, 60]. Quantization increases the network's lifetime and reduces the total bandwidth used. However, this causes a degradation in estimation accuracy[41, 69]. When quantization is used, the error becomes highly dependent on the total number of bits used as well as their allocation among the sensors and the targets. This is especially true when sensors are not uniformly distributed and the number of bits allowed is relatively small[68, 2, 31]. In the sensor selection problem, either a sensor is selected for the transmission of targets' data or a sensor is not selected. The sensor selection problem's constraint is either the maximum number of active sensors we can choose from or the maximum amount of bits we can allot to those sensors. If a sensor is not selected, that means it does not transmit any information about the targets to the FC. If a sensor is selected because it has the most useful data about the targets, either it communicates all the data about every target that is in its coverage area or it transmits a fixed number of bits for all targets, irrespective of any sensor or target properties, to the FC. The important difference between the sensor selection problem and the proposed dynamic distribution of bits to the targets is that each target could be assigned a different number of bits rather than communicating the entire measurement set or allocating the same fixed number of bits without considering any sensor or target properties. So each target at the sensor may be assigned a different number of bits by considering target and sensor characteristics. For instance, targets with great manoeuvrability may require more bits than targets without manoeuvrability. The proposed improved dynamic allocation approach can also be applied following the sensor selection process for better bit allocation to the targets and within the measurement elements.

There are several sensor selection algorithms in the literature, and a bit allocation has been previously studied. We first briefly discuss the related work before outlining the differences between our work presented herein and the work in the literature. In [45], the dynamic bandwidth allocation problem for single target tracking based on quantized sensor data in wireless sensor networks was studied. Under the sum rate constraint, an approximate dynamic programming (DP) algorithm that maximizes the Fisher information by maximizing its determinant was proposed. However, the optimal solution is computationally intensive and cannot be applied to practical systems. Therefore, various suboptimal solutions have been proposed, including convex optimization and other heuristic algorithms such as greedy methods. Greedy algorithms have also drawn much attention for other forms of sensor selection problems, where the FC desires the maximum likelihood (ML) or maximum a posteriori (MAP) estimate of the unknown vector. Only a subset of the sensors that acquire the measurement is allowed to transmit its measurement to the FC[67]. In [19], under the assumption that the components of the measurement noise vector are uncorrelated with each other, the PCRLB for state estimation problems with quantized measurements is proposed for certain application scenarios. The PCRLB is also a very important tool because it provides a theoretical performance limit for a Bayesian estimator. In[91], the one-step look-ahead posterior Cramer-Rao Lower Bound (CRLB) on the state estimation error is proposed as the sensor selection criterion. A sensor selection strategy that reduces the PCRLB on the estimation error has been presented for single target tracking and in a bearing-only sensor network, where the chosen sensors communicate quantized data to the fusion center. In [1], two novel low complexity allocation algorithms are proposed for a rate-constrained bit allocation problem in which multiple points of interest (PoIs) are assigned possibly non-uniform error requirements. The important point behind these algorithms is to associate localization errors with corresponding bit density requirements. The sensor selection problem is always formulated as an optimization problem based on different optimization objectives, such as estimation accuracy, energy efficiency, or other key performance indicators. The sensor selection problem for target localization and target tracking has been considered in [91] among others, where the sensor sets are selected to get the desired information gain or a decrease in the target state's estimation error. For the sensor selection problem based on quantized data, the authors in [44] compared the two sensor selection criteria, mutual information (MI) and PCRLB, and demonstrated that the PCRLB-based sensor selection scheme achieves a similar mean square error (MSE) with a sizably reduced computational effort. Optimal quantization schemes at sensor nodes under strict energy constraints are derived in [39]. Optimality here is in terms of minimizing a bound on the mean-absolute reconstruction error at the FC Besides adaptive quantization and other interesting strategies, such as protecting different bits with different bit error rates have been discussed. Fusion of quantized measurement via particle filtering is discussed in[63]. Nevertheless, adaptive quantization thresholds are not taken into account in the paper, therefore, performance can be improved by using quantization using dynamic bit allocation. Particle filtering is an interesting way to allow for the non-Gaussian measurement noise accruing from quantization. In a system that uses quantized measurements, estimating the system state is a nonlinear and non-Gaussian estimation problem even if the system is linear and Gaussian because of the nonlinearity of the quantizer. A numerical algorithm for approximate minimum mean square error (MMSE) state estimation with quantized measurement was proposed in [20]. Several quantization philosophies are explored in [42], specifically, uniform quantization, uniform quantization with measurement exchangeability incorporated (the "type" method), and uniform quantization of sorted measurements. The sensor selection problem for parameter estimation with correlated measurement noise has been proposed in [37]. A multi-objective optimization framework for the sensor selection problem in uncertain Wireless Sensor Networks was proposed, and a novel mutual information upper bound (MIUB)-based sensor selection scheme, which has low computational complexity, same as the Fisher information (FI)-based sensor selection scheme, and gives an estimation performance similar to the mutual information-based sensor selection scheme [11]. In [47], a two-step optimization procedure is proposed for dynamic bit allocation for target tracking. First, the best time-independent quantizers are obtained offline by maximizing the average Fisher information about the signal amplitude, for a different number of bits. Using the time-independent quantizers, the generalized Breiman, Friedman, Olshen, and Stone (BFOS) algorithm is applied to dynamically assign bits to sensors.

The primary distinctions between the proposed dynamic approach of the bit distribution, which is presented herein, and the work listed in the literature are: 1) Since different sensors have different properties, such as range accuracy and azimuth accuracy, we choose the most meaningful information from most of the sensors rather than choosing some sensors, especially when the sensors share the tracking zone. 2) We take into account the bandwidth at the FC and the sensor node rather than just the FC bandwidth. 3) We distribute the bits in an adaptive manner to all the targets at the sensor node, instead of choosing the complete measurement or the fixed bits for each measurement. 4) We consider multiple targets and more than one element in a measurement as an alternative to a measurement vector of size one. For instance, a measurement vector is of size two if it has range and azimuth. A measurement is of size three if it has range, azimuth, and elevation as its elements. 5) As a substitute for sending the entire measurement, we send the difference of measurement from the previous scan to the current scan to reuse the information from previous scans in addition to reducing the error due to quantization. This method is particularly useful if the target is travelling at the same speed or in the same direction. 6) Sharing of tentative track information from multiple sensors that are in a shared region with more than one sensor for rapid initialization of tracks. The contributions of this paper are listed below.

- Formulation of the bit allocation problem as a multi-objective integer optimization problem that minimizes the PCRLB over all the targets and meets the given bandwidth constraints. This ensures that resource allocation is done to targets instead of sensors, thereby optimizing limited bandwidth.

- Consideration of bandwidth constraints both at the FC as well as at each sensor node in the formulation of dynamic bit allocation.

- An approximate bit allocation algorithm that allocates bits to each of the targets at the fusion center as well as distributing bits between elements within the measurement vector.

- Fast target initialization in the shared region of interest (SROI) by communicating the tentative tracks from multiple sensors in the SROI.

- Demonstration of the effective use of non-uniform quantization over uniform quantization for measurement quantization.

The remainder of the chapter is organized as follows. The problem formulation and system model are given in Section 2.2 Details of uniform and non-uniform quantization methods are provided in Section 2.3. PCRLB derivation utilizing quantized measurements is discussed in Section 2.4. The proposed approximation algorithm is elaborated in Section 2.5. In Section 2.6, performance analysis is reported. Finally, conclusions are reached in Section 2.7.

2.2 Problem Formulation

The bits are assigned to each target in a manner that minimizes the PCRLB at the fusion center instead of choosing the sensor or assigning the bits to each sensor. The bits are efficiently allocated to each of the measurement elements if the measurement consists of more than one element. The objectives of the resource allocation problem are 1) to make effective use of available resources and 2) to obtain good tracking performance by making the best use of resources. The allocated bits for each target are efficiently allocated to each of the measurement elements if the measurement consists of more than one element.

2.2.1 System Model

A two-dimensional region of interest (ROI) with dimensions $a \times a$ is considered. The ROI includes a few SROIs. A total of N sensors are deployed in the ROI, and their positions are $\{s_n = [x_n, y_n]', n = 1, 2, ..., N\}$. The sensor positions and their characteristics are known at the FC. These sensors may be of different types, with sensing radius R_s meters. Furthermore, we assume that due to bandwidth and energy restrictions, each sensor can only communicate one measurement for each track. Each sensor runs a local tracking algorithm to select the best measurement for each track using a data association algorithm. Finally, it is evident that the estimation error and the bit availability at the FC and at each sensor node are inversely proportional. The fewer bits available, the larger the resulting estimation error, and vice-versa. We consider an unknown number of targets moving in a 2-D cartesian coordinate plane according to a linear dynamic white noise acceleration model Equation 2.2.1

$$X_{k+1} = FX_k + v_k \tag{2.2.1}$$

where the constant parameter F is the state transition matrix. $X_k = \{X_k^1, X_k^2, ..., X_k^M\}$ is the stacked state vector of all the targets at time k. X_k^t is the target state of target t at time k is defined as $X_k^t = [x_k^t, y_k^t, \dot{x}_k^t, \dot{y}_k^t]^\top$, x_k^t and y_k^t are the target positions, $\dot{x}_k^t$ and $\dot{y}_k^t$ denote the velocities in horizontal and vertical directions. v_k is white Gaussian process noise with zero mean and covariance matrix Q. The measurements originate from either targets or clutter. The target-originated measurement for the sensor s at time k is given by

$$y_k^s = \begin{cases} h_k^s(x_k) + w_k^s, \text{ with probability } \ p_k^s \\ w_k^s, \text{ with probability } \ (1 - p_k^s) \end{cases} \tag{2.2.2}$$

where p_k^s is the sensing probability of sensor s at time k, h_k is a non-linear mapping function from the state space to the measurement space that includes range, bearing, and w_k is the measurement noise at time k. Due to power and bandwidth limitations, each activated sensor quantizes its measurements into a finite bit message as

$$z_k^s = \mathcal{Q}(y_k^s), s = 1, 2, 3, ..., N \tag{2.2.3}$$

where z_k^s is a quantized measurement vector and the quantizer $\mathcal{Q}$ is a nonlinear mapping.

$$z_k^s = \{z_k^s(i)\}_{i=1}^{m_k^s} \tag{2.2.4}$$

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, Q = q \begin{bmatrix} \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^2}{2} & 0 & T \end{bmatrix} \tag{2.2.5}$$

where T is the sampling interval and q is the process noise parameter. Given N number of sensors, and each sensor has m_k^s measurements. m_k^s is a random quantity. In order to reduce the cost of communication, each sensor measurement z_k^s is quantized into b_k^s bits before transmission to the FC. $b_k^s \in \{0, 1, 2, 3, ..., D_{max}\}$ where D_{max} is the maximum number of bits any measurement can use. The quantized measurement z_k^s of sensor s at time step k, is τ_k^s which is defined as:

$$\tau_k^s = \begin{cases} 0, & \eta 0 \leq z_k^s \leq \eta 1 \\ 1, & \eta 1 \leq z_k^s \leq \eta 2 \\ . & \\ . & \\ . & \\ (L-1) & \eta(L-1) \leq z_k^s \leq \eta L \end{cases} \tag{2.2.6}$$

where $\eta = [\eta 0, \eta 1, ..., \eta L]^\top$ is the set of quantization thresholds with $\eta 0 = -\infty$ and $\eta L = \infty$ and $L = 2^{b_k^s}$ is the number of quantization levels for each measurement. In general, the only point we can infer from a quantized measurement $Z_k = i$ is about the measurement before quantization y_k is

$$\eta_i \leq z_k \leq \eta_{(i+1)}$$

where η_i and $\eta_{(i+1)}$ are quantization thresholds. We have two optimization problems, one at the FC and another at the sensor nodes. The optimization issue at FC is solving for the bits for all the targets. The main purpose of the second optimization challenge is to handle the mis-detections and redistribute the bits to other targets instead of not sending any information.

2.2.2 Optimization Problem Formulation at the Fusion Center

We consider a one-step ahead scenario, where at a given time step, the fusion center only decides on the bit allocations for the next time step. The FC distributes the bits optimally and dynamically among the activated sensors and all tracks. Dynamic bit allocation provides better estimation performance as compared to sensor selection schemes or fixed bit allocation since it distributes the resources more efficiently by considering sensor characteristics and track trajectory. As shown in Fig.2.1, the fusion node calculates the optimum number of bits for each track by optimizing the target tracking performance and sends the allocation information to each sensor node. In this architecture, all the sensors are connected to a central FC that fuses all the measurements and updates the tracks. Then each sensor uses uniform or non-uniform quantization to encode the measurements of each target according to the bit allocation. We can effectively divide the problem formulation into two cases based on the available information at the FC. The first case is where the FC has all the information about the number of confirmed tracks, new tracks, and tentative tracks. The second case is where FC does not have all the information about the number of new tracks and tentative tracks in the shared region.

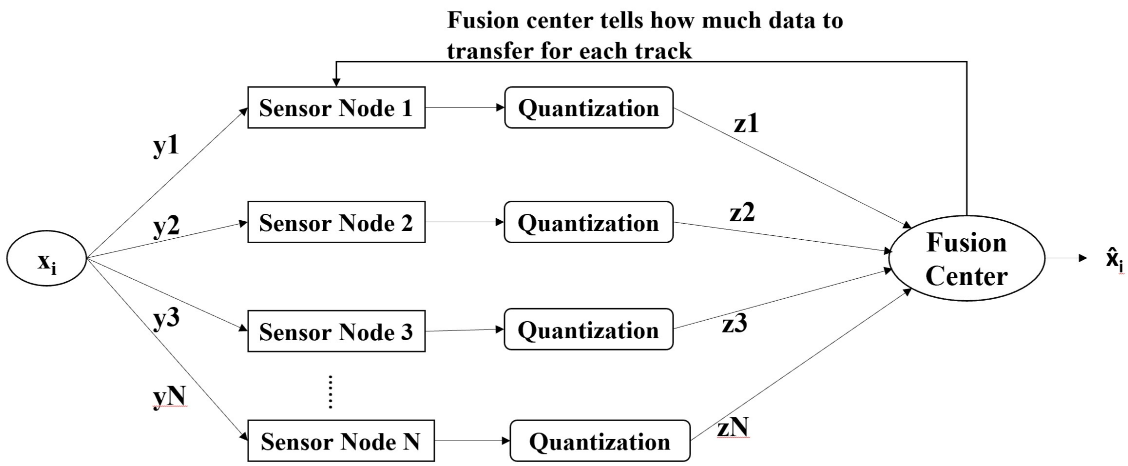


Figure 2.1: Distributed fusion architecture for target tracking with quantized measurements

case 1: In this case, FC has the required information about the number of confirmed tracks, new tracks, and tentative tracks. The main objective is to minimize the estimation error and maximize the reward value of all the sensors. The reward value is defined as the difference between the FC's allocated bandwidth and the actual bandwidth used by the sensor for each target. Each sensor node communicates the incremental change in the measurement for confirmed tracks, which improves measurement error due to quantization. For instance, for already existing confirmed tracks, instead of sending $< r, \theta >$ we send quantized $< \Delta r, \Delta\theta >$, where r is the range and θ is the bearing angle, and Δr is the incremental range in meters and $\Delta\theta$ is the incremental heading angle in degrees. Overhead is the amount of bandwidth required for the extraction or decoding of the measurements at the FC. Let CT, NT, and TT be confirmed tracks, new tracks, and tentative tracks in the shared region(SROI) respectively. The constraint $C1$ in equation 2.2.9 is on total bandwidth availability at the FC, and $C2$ in equation 2.2.10 is on the availability of bandwidth at each sensor.

$$\begin{aligned} &\textbf{PCRLB, F1: min}(\sum_{i=1}^{M} w_i \det(E[\hat{x}_i - x_i][\hat{x}_i - x_i]^\top)) \\ &\textbf{Reward, F2: max } (B_{max} - B_M) + \sum_{s=1}^{N} w_s(B_s - B_f^s) \end{aligned} \tag{2.2.7}$$

$$\begin{aligned} &\textbf{Obj: min}(W1 * F1 + W2 * (-F2)) \\ &\text{where } W1 + W2 = 1 \end{aligned} \tag{2.2.8}$$

- B_{max} is total bandwidth available at FC.
- B_s is the bandwidth available at sensor s.
- B_f^s is allocated bandwidth by the FC to sensor s.
- N is a number of sensors, M is a number of tracks.

Subject to

$$\textbf{C1: } B_M + \sum_{s=1}^{N} \text{Overhead}^s \leq B_{max} \tag{2.2.9}$$

$$\textbf{C2: } B_f^s + \text{Overhead}^s \leq B_s \;\; \forall s = 1, 2, 3, ..., N \tag{2.2.10}$$

$$\begin{aligned}
B_f^s &= B_{ct}^s + B_{nt}^s + B_{tt}^s & B_{tt}^s &= \sum_{t=1}^{tt}\sum_{j=1}^{m} D_t^s(j) \\
B_M &= B_{CT} + B_{NT} + B_{TT} & B_{CT} &= \sum_{s=1}^{N} B_{ct}^s \\
B_{ct}^s &= \sum_{i=1}^{ct}\sum_{j=1}^{m} D_i^s(j) & B_{NT} &= \sum_{s=1}^{N} B_{nt}^s \\
B_{nt}^s &= \sum_{n=1}^{nt}\sum_{j=1}^{C}\sum_{q=1}^{m} D_n^s(j_q) & B_{TT} &= \sum_{s=1}^{N} B_{tt}^s
\end{aligned} \tag{2.2.11}$$

- B_M Total bandwidth allocated to all tracks for all sensors.
- B_{CT},B_{NT}, and B_{TT} are bandwidth allocated to confirmed tracks, new tracks, and tentative tracks, respectively.
- m is the measurement vector size.
- C is the number of measurements required for track initiation at FC.
- B_{CT} is bandwidth allocated to all confirmed tracks at FC.
- B_{NT} is bandwidth allocated to all new tracks at FC.
- B_{TT} is bandwidth allocated to all tentative tracks at FC.
- B_{ct}^s is bandwidth allocated to all confirmed tracks at the sensor s.
- B_{nt}^s is bandwidth allocated to all new tracks at the sensor s.
- B_{tt}^s is bandwidth allocated to all tentative tracks at the sensor s.

Constraint C1 includes the bit distribution within the measurement. For instance, if a measurement consists of range and bearing, in some cases, we may need just range or only bearing to compute the next target state. If a target is moving in the same direction, then we can only send a change in the range value. Suppose some sensors are more accurate in measuring bearing than range, the optimization problem helps to assign more bits to bearing for those sensors than others, which in turn improves the PCRLB. Each sensor only can transmit limited data due to power or energy restrictions, which are represented by C2. Here B_{max} is the bandwidth limit per frame in bits, for example, $B_{max} = 60$ bits, and D^s_{ct} is the bandwidth allocated by each FC to each track at each sensor s, B_s is the bandwidth limit for each sensor s which in turn depends on the locally available energy. d^s_{ct} is the actual used bandwidth by each sensor. Each sensor is awarded reward points if it uses less bandwidth than the bandwidth allocated by the FC. Let m be the measurement vector length. As an illustration, m equals 3 if a measurement consists of range, elevation, and bearing. PCRLB is to be derived for state estimation using quantized measurements.

case 2: Suppose sensor nodes won't communicate to FC the number of new tracks and tentative tracks in the shard region. The FC can allocate a portion of bandwidth to newly confirmed tracks based on the birth rate and the death rate. Due to the large number of deployed sensors, they frequently share a common Region Of Interest (ROI). As shown in Fig.2.2 there are three sensors and seven targets, and target 4 (T_4) is in the shared region of all three sensors. T_2 is in the shared region of sensor 1 and sensor 2. The FC can fast initiate a track in a shared region if each sensor can report tentative tracks in the shared region by using information from all the contributing sensors[4, 5]. We define confirmed track as 3/4 hits(3 track to measurement associations out of 4 continuous scans) and tentative track as 2/2 hits logic at each sensor node. To prioritize the tentative tracks in the SROI sensor nodes, send the number of tentative tracks in the shared region. For new tracks, we send a total C number of measurements, where C is a measurement count, which is defined as the total number of measurements required by the FC to initiate a new track. In typical scenarios, initializing the track may require at least two measurements. Each measurement vector is of length m. For example, if a measurement has range and azimuth, the value of m is set to two.

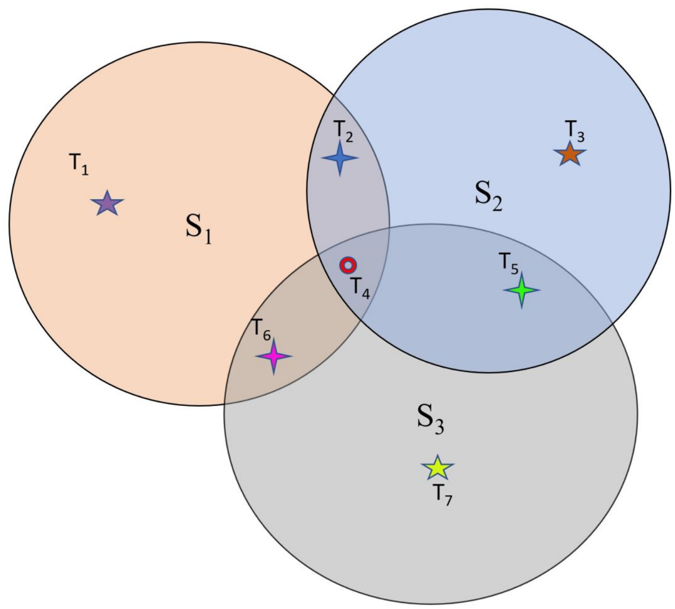


Figure 2.2: Multi-Sensor Multi-Target tracking

$$\textbf{F2:}\ \ \textbf{max}\ (B_{max} - (B_{CT} + B_{min})) + \sum_{s=1}^{N} w_s(B_s - (B_{ct}^s + B_{min}^s)) \tag{2.2.12}$$

$$\begin{aligned} &\textbf{C1:}\ \ B_{CT} + B_{min} \leq B_{max} \\ &\textbf{C2:}\ \ B_{ct}^s + B_{min}^s + \text{Overhead}^s \leq B_s\ \ \forall s = 1, 2, 3, ..., N \end{aligned} \tag{2.2.13}$$

$$B_{min} = \sum_{s=1}^{N} B_{min}^{s} \tag{2.2.14}$$

$$B_{min}^{s} = \lambda_b^k \sum_{q=1}^{C} \sum_{m=1}^{M} D_n^s(q_m) \tag{2.2.15}$$

$$\begin{aligned} \lambda_b^k &= \frac{\lambda_b}{\lambda_\chi}(1 - exp(-\lambda_\chi * (t_k - t_{k-1}))) \\ P_\chi^k &= (1 - exp(-\lambda_\chi * (t_k - t_{k-1}))) \end{aligned} \tag{2.2.16}$$

- B_{min}^{s} is the minimum bandwidth reserved for new tracks at sensor s.
- B_{min} is the minimum bandwidth reserved for new tracks for all sensors.
- λ_b is the continuous birth rate of a sensor.
- λ_b^k defines the effective birth rate of a sensor at the time interval (t_k, t_{k-1}).
- λ_χ is the death rate under an exponentially-distributed target life.
- P_χ^k defines the probability of death during (t_k, t_{k-1}).

2.2.3 Optimization Problem Formulation at the Sensor Node

A local optimization technique at the sensor node's main objective is to effectively assign the extra available bits to local tracks in the event of mis-detections. Each sensor maintains its own track of all targets, and associated measurement reports (AMR) are shared with FC to get a global estimate. In the event of mis-detections, each sensor node employs a local optimization technique to effectively allocate the bits to local tracks. Due to the low bandwidth and frequent measurements, we assume that the local sensor node sends just one measurement for each track. If there are mis-detections then the local optimization problem is able to redistribute the bandwidth allocation to improve estimation by maximizing the local fisher information at the same time while maintaining the priority of each track given by the FC. The number of bits allocated to each target at FC stays the same or increases due to the local optimization problem at the sensor node. The additional bandwidth is reallocated in a manner that maximizes the local Fisher information by utilizing the given bits for the tracks at a given sensor node. Let LT be the number of local tracks, and the fusion node assigns D_i^s bits for each track $i \in \{1, 2, ..., LT\}$ for sensor s, and the new assignment is d_i^s by the local sensor node. We can limit the number of tracks to redistribute the extra available bits due to the overhead involved. Here, J_i is the Fisher Information for the local track i, tr is a trace of a matrix, and LT is the total number of local confirmed tracks. The objective function is the summation of functions 1 and 2 with given weights W1 and W2.

$$\begin{aligned} &\textbf{F1: Max} \sum_{i=1}^{LT} w_i \det(J_i) \\ &\textbf{F2: Max } (B_s - \sum_{i=1}^{LT} \sum_{j=1}^{m} d_i^s(j)) \text{ where } s \in 1, 2, 3, ..., N \end{aligned} \tag{2.2.17}$$

$$\textbf{Obj: min}(W1 * (-F1) + W2 * (-F2))$$

$$w_i = \frac{D_i}{\sum_{j=1}^{LT} D_j} \text{where } \; i \in \{1, 2, ..., LT\} \tag{2.2.18}$$

$$\text{where } \; W1 + W2 = 1$$

Subject to

$$\begin{aligned}
&\textbf{C1: } d_i^s \begin{cases} \geq D_i^s, & \text{if there is a measurement for track i} \\ = 0, & \text{in case of misdetection} \end{cases} \\
&\textbf{C2: } \sum_{i=1}^{LT} \sum_{j=1}^{m} d_i^s(j) + \text{Overhead}^s \leq B_s \text{ where } s \in 1, 2, 3, ..., N
\end{aligned} \tag{2.2.19}$$

- D_i^s is the number of bits allocated by FC for target i at sensor s.
- LT total number of local tracks at a sensor.
- d_i^s is the number of bits communicated to the FC for each track i at the sensor s after solving the optimization problem.

2.3 Uniform and Non-Uniform Quantization

Sharing measurements directly with the FC is preferred to sharing local estimates at the sensor node since, in the former scenario, some type of ideal fusion is attainable[57]. The measurements of the tracks at each sensor node need to be communicated to FC with high computational resources to get the global picture of the tracking region. Due to limited energy and communication capability, each sensor node compresses the data before sending it to FC. Even though quantization reduces the amount of data to be communicated to FC, it gives poor tracking performance due to the loss of information. Non-uniform quantization of information with the given allocated bits is an effective way to reduce quantization error. A scalar quantizer partitions the set $\mathbb{R}$ of real numbers into M subsets $R_1, R_2, ..., R_M$, called quantization regions, and each quantization region is an interval. We first have to find out how to choose the quantization regions $R_1, R_2, ..., R_M$, and the corresponding representation points. Each region R_j is then represented by a representation point $a_j \in \mathbb{R}$. When the source produces a number $u \in R_j$, that number is quantized into the point a_j as shown in Fig.2.3. A scalar quantizer can be viewed as a function that maps analog real values into discrete real values. After the allocation of bits using dynamic bit allocation, we can either use uniform or non-uniform distribution. When a variable's range is wide, uniform quantization performs poorly. When the variable's distribution is known, non-uniform distributions perform better, even when the range is large[30]. A combination of dynamic allocation of bits and non-uniform quantization gives good tracking performance. For instance, we can effectively quantize the data using nonuniform quantization and reduce quantization error if we are aware of a sensor's range or azimuth distribution. We can utilize either user-defined distributions or common probability distributions, such as the Bernoulli, Uniform, Binomial, Normal, Poisson, Chi-square, and Exponential Distributions.

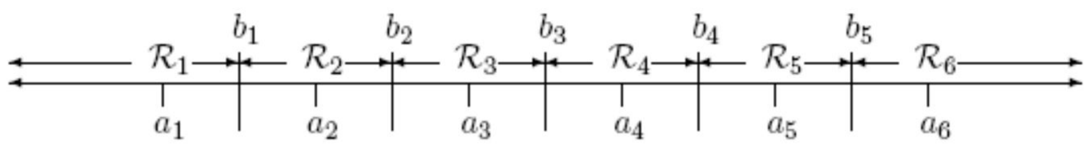


Figure 2.3: Quantization regions and representation points.

Even though quantization reduces the amount of data to communicate to FC, it causes an additional error due to quantization, which is called Mean-square quantization Error. The expected mean-square quantization error σ_Q^2 can be represented in terms of the quantization error in each interval $\sigma^2_{Q,i}$.

$$\sigma_Q^2 = \sum_{t=1}^{L} \sigma^2_{Q,i} p_i, \quad \sigma_Q^2 = \frac{1}{12} \sum_{t=1}^{L} \Delta_i^2 p_i \tag{2.3.1}$$

Δ_i: ith step size of the given nonuniform quantizer.

p_i : the probability that the input variable lies within the ith interval.

L is the number of quantization levels. $L = 2^n$ if n is the number of allocated bits.

2.4 PCRLB Derivation Using Quantized Measurements

PCRLB provides the theoretical performance limit for a Bayesian estimator. The covariance of X_k is bounded below by the recursive PCRLB, which is defined to be the inverse of the Fisher Information Matrix (FIM) J_k. Let $\hat{X}_k$ be an unbiased estimator of the state vector X_k.

$$E[\hat{X}_k - X_k][\hat{X}_k - X_k]^\top \geq J_k^{-1} \tag{2.4.1}$$

Fisher information matrix, $J = J_{prior} + J_z$ which is the inverse of PCRLB, where J_{prior} is prior information and J_z is measurement information about the target at a given time.

$$\begin{aligned} &J_0 = {P_0}^{-1} \\ &J_{prior} = (Q_{k-1} + F_{k-1} J_{k-1}^{-1} F_{k-1}^\top)^{-1} \\ &{J_k}^{-1} = (J_{prior} + H_k^\top R_k^{-1} H_k)^{-1} \end{aligned} \tag{2.4.2}$$

It has been shown that the FIM for Bayesian estimation is composed of two parts: the FI obtained from the sensor measurements and the FI corresponding to a priori information. Furthermore, under the assumption that the sensor measurements are conditionally independent, given the target state X_k, the FI obtained from the measurements of multiple sensors can be written as the summation of each sensor's FI plus the FI from the prior information.

$$J_k \triangleq \sum_{i=1}^{N} \int_{X_k} J_{i,k}^{S}(X_k)p(X_k)dX_k + J_k^P \tag{2.4.3}$$

where J_k^P is the FI matrix of the a priori information, and $J_{i,k}^S$ represents the standard FI of each sensor as a function of the target state X_k,[47]

$$\begin{aligned} J_{i,k}^{S}(X_t) &= \int_{z_{i,k}} \frac{1}{p(z_{i,k}|X_k)} \left(\frac{\partial p(z_{i,k|X_k})}{\partial X_k}\right) \left(\frac{\partial p(z_{i,k|X_k})}{\partial X_k}\right)^{\top} dz_{i,k} \\ J_{i,k}^{S} &= \frac{1}{2\pi R_k^i [h_k^i(X_k^j)]^2} \phi_k^i(X_k^j) \times \\ &\begin{bmatrix} (x_i - x_k)^2 & (x_i - x_k)(y_i - y_k) & 0 & 0 \\ (x_i - x_k)(y_i - y_k) & (y_i - y_k)^2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{aligned} \tag{2.4.4}$$

where $\phi_k^i(X_k^j)$ can be calculated as

$$\phi_k^i(X_k^j) = \sum_{l=0}^{L-1} \frac{\left\{ e^{-\frac{[\eta_l - h_k^i(X_k^j)]^2}{2R_k^i}} - e^{-\frac{[\eta_{l+1} - h_k^i(X_k^j)]^2}{2R_k^i}} \right\}^2}{p(Z_k^i = l|X_k^j)} \tag{2.4.5}$$

The most common and perhaps the simplest approach is to approximate the effect of quantization as an independent additive uniform noise ε_k as follows

$$\begin{aligned} z_k &= H_k x_k + \underbrace{v_k + \varepsilon_k}_{\tilde{v}_k} \\ \varepsilon_k &\sim \mathcal{U}(a_k, b_k), E[\tilde{v}_k] = 0 \\ \tilde{R}_k &= cov[\tilde{v}_k] = R_k + \sigma_Q^2, \text{ where } \sigma_Q^2 = \frac{\Delta^2}{12} \end{aligned} \tag{2.4.6}$$

If the measurement range is $[R_{min}, R_{max}]$ and the quantization scale(Δ) is determined by the number of bits allocated to it by using uniform quantization. If the number of bits allocated is b, then

$$\Delta = \frac{(R_{max} - R_{min})}{2^b} \tag{2.4.7}$$

Measurement error due to quantization, Δ depends on the number of bits allocated and also the maximum and minimum values of the measurement. We can improve Δ by sending incremental change in the measurement rather than the actual measurement, as at each scan the maximum incremental change shall be comparatively much less than the actual value of the measurement, which in turn reduces the quantization scale value. For non-uniform quantization, the error is calculated using Equation 2.3.1.

2.5 Approximation Algorithm

An essential issue for information fusion is to allocate bandwidth to tracks, which can maximally reduce the uncertainty about the events of interest with minimum costs. Dynamically determining the best allocation of bandwidth, given the uncertainty about the state of the world, requires enumerating all the possible subsets of bit allocation, which is computationally intractable and practically infeasible. The computation of bandwidth allocation is exponential, and it is an NP-hard problem. To address this computational difficulty, a common practice is to use an approximate algorithm. So we propose a low-cost, suboptimal solution that can be implemented and run in real time. Given the total bandwidth available, the bandwidth available for each sensor, and the total number of confirmed tracks at the FC. The main intuition behind the approximate algorithm is to prioritize the tracks based on their contribution to fisher information using prior information and a fixed number of bit allocations for all tracks. If the track is contributed by multiple sensors, the highest contributing sensor's Fisher information is used to calculate the priority of the track. Once the bits are allocated to each track for each sensor, the distribution of bits within the measurement is done using the incremental change in the measurement vector. For instance, if a measurement consists of range and azimuth, the weighted average is used to distribute the bits between range and azimuth. If the incremental change in the azimuth is zero, then all the bits are allocated to the range, and vice versa. The detailed algorithm is described in Algorithm 1.

2.6 Performance Analysis

To analyze the dynamic bit allocation method, we compare the results with those of fixed bit allocation. The fixed bit allocation is where the FC and sensor nodes equally distribute the available bandwidth between the targets and within the measurement. For instance, if FC has 40 bits and two sensors are associated with it, then each

Algorithm 1 Approximation Algorithm

Require: Let M be the number of tracks at the FC, and N contributing sensors, each with prior fisher information J_p at scan time t.

Ensure: Bandwidth distribution for all tracks.

1: Compute J_z for each of the M tracks,$J_z = H_{k+1}^{\top} \tilde{R_k}^{-1} H_{k+1}$ where $\tilde{R}_k$ can be approximated to $\tilde{R}_k = R_k + \frac{\Delta^2}{12}$, Δ is calculated using, static number of bits(μ).

2: Calculate FIM $J = J_p + J_z(\mu)$ for each track using static number bit(μ bits) allocation to each of the contributing sensors. It means J_i is a reward in terms of fisher information when track i quantizes using μ bits.

3: If a track is contributed by more than one sensor, the highest contributing sensor's reward is taken into consideration to calculate the weight of a track.

4: Let reward of track i is $A(i) = \det\{J_i\}$.

5: Calculate the normalized weight w_i of all tracks using $w_i = \frac{A(i)}{\sum_{j=1}^{s_i} A(j)}$

6: Allocate the bandwidth to the highest priority track (i^*), using w_i and available bandwidth at the FC. Let m be the number of contributing sensors for track i^*, the maximum available bandwidth for track i for all contributing sensors is $\sum_{j=1}^{m} B_m$

$$i^* = \arg\max_{c \in M} A(c)$$

$$B_{i^*} = w_{i^*} \times B$$

7: The allocated bandwidth is distributed to the contributing sensors of track i^* according to the information contribution from each sensor. $A(i_s)$ is the reward of the sensor s, and bandwidth allocation to the sensor s is

$$B_{i^*}(s) = \frac{A(i_s)}{\sum_{n=1}^{m} A(i_n)} \times B_{i^*}.$$

8: If $B_s < B_{i^*}(s)$ then, $(B_s - B_{i^*}(s))$ bits will be allocated to the next priority sensor.

9: Distribute the bandwidth within the measurement. Let ν be the measurement vector size, each with accuracy $\phi_k, k \in \nu$. We use the previous scan's measurement change to distribute the bits for the next scan. Let β be the recent change in the measurement. Calculate the weight for each element in the measurement $q \in \nu$ as $w_q = \frac{\beta}{\phi}$.

10: Calculate the normalized weight w_q of each element in the measurement. $w_q = \frac{w_q}{\sum_{j=1}^{\nu} w_j}$ and allocate $w_q \times B_{i^*}(s)$ to the measurement element q.

11: Update the total available bandwidth at the FC and each of the sensors' bandwidths. $B = B - B_{i^*}$, $B_s = B_s - B_{i^*}(s)$.

12: If there are any unallocated bits of the target, they will be assigned to the next priority target.

13: Repeat from step 6 until the allocation of bandwidth for all tracks. Remove the track i^* from the list of tracks to allocate the bits. $M = M - i^*$.

sensor is assigned a bandwidth of 20 bits, and if the sensor has two targets, each target is assigned 10 bits. If the measurement consists of the range and azimuth, 5 bits are assigned to the range and 5 bits to the azimuth. To solve the optimization problem, a Genetic Algorithm (GA), implemented in MATLAB, is used. For uniform quantization, the quantization error is approximated to $\Delta^2/12$. We assume that each sensor can only transmit one measurement for a confirmed track. We use the Global Nearest Neighbour (GNN) data association to select one measurement for each confirmed track. We used history-based confirmation logic (N out of M), if the track has been assigned N(2) detections out of M(4) it will be confirmed. For the first two scans after the track confirmation, we assigned fixed bits for both fixed and dynamic methods. Once the track is established, we send only the incremental change in the measurement. For each mis-detection at each sensor node, the extra bits are assigned to the highest priority target based on information contribution using the approximate algorithm. FC has full information about the sensor nodes, like their position and their characteristics. Intelligent quantization requires that both the sensor and the FC share an understanding of the quantization rule. If there are no mis-detections, there won't be extra overhead apart from the bits required to send the track number and sensor number, as the FC has information on the number of bits for the range and azimuth of each track. If there are mis-detections, the header part of the mis-detected track bits is used to indicate the change in the number of bits in range and the azimuth of the new allocation at the sensor node to the FC. We made the assumption in simulations that the header portion of the mis-detected track bits would be adequate to indicate the modification in the new bit allocation.

2.6.1 Case 1:

The purpose of this experiment is to demonstrate the effective bit distribution inside the measurement using the dynamic bit distribution between azimuth and range. In this experiment, we have one sensor and one target. As shown in Fig.2.4, the track is moving away from the sensor. In Fig.2.5, we show the RMSE comparison between dynamic bit allocation and fixed bit allocation. The improvement in RMSE comes from the effective distribution of bits between range and azimuth. In Fig.2.6, we demonstrate the bit allocation for range and azimuth. In order to achieve superior RMSE performance depending on a trajectory for the given track, the dynamic bit allocation technique allotted more bits to range than azimuth. In Fig.2.7, we have compared uniform and non-uniform quantization errors for a Gaussian variable and a Rayleigh distributed variable using a fixed number of bits and observed that we can get a significant gain by using non-uniform quantization if the range of the variable is large. In Fig.2.8, we have compared the RMSE using uniform and non-uniform quantization by assigning the same number of bits for both. For non-uniform distribution, we take advantage of the sensor's known range and azimuth distributions. For instance, if we are measuring the temperature of a specific area, and we know the temperature will likely range between 0 and 20 in Celsius with some known distribution, we can use this information for the non-uniform quantization. Measuring the height or altitude of flying objects like airplanes is another example, where typically the value lies between 20,000 and 40,000 feet. The results show that non-uniform quantization yields good performance. For this experiment, 500 Monte Carlo simulations were used. Therefore, even with minimal bandwidth utilization, the proposed dynamic bit allocations in combination with non-uniform distribution provide the highest potential performance. Simulation parameters and simulation setup:

- Number of Sensors: 1
- Number of Targets: 1
- Bandwidth available at FC (in bits): 10
- Bandwidth available at the sensor: 6
- Sensor range error: 10
- Sensor azimuth error: 0.01
- Probability of Detection: 0.9
- False Alarm Density: 1e-4
- Sensor Maximum Range: 2000
- Sampling Time: 1
- Initial Fisher Information Matrix $J_0 = {P_0}^{-1}$

2.6.2 Case 2:

In this experiment, we show that using more than one sensor to share information is advantageous compared to using just one. We have two sensors and one target, and the target is in the shared region of the two sensors. In terms of range accuracy, sensor 1 was superior to sensor 2, whereas sensor 2 was superior in terms of azimuth accuracy. The results show the effective distribution and sharing of bits among the

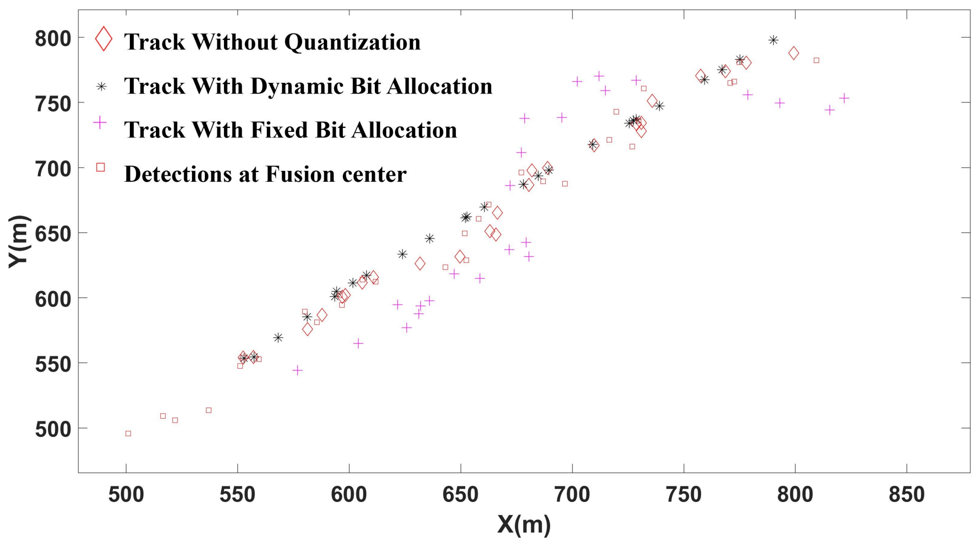


Figure 2.4: Target Trajectory with one sensor and one Target

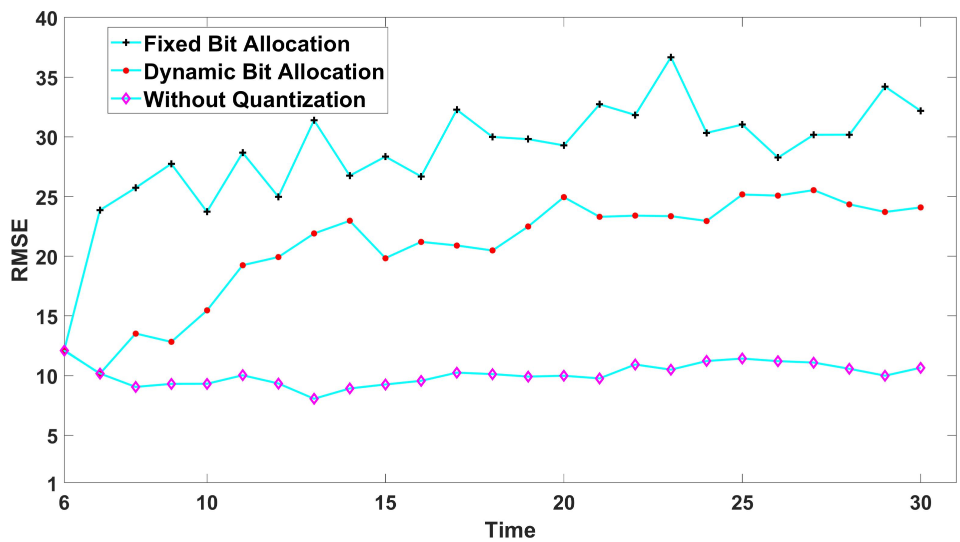


Figure 2.5: Comparison of RMSE using Dynamic bit allocation, Fixed bit Allocation, Without Quantization (Using GNN Data Association)

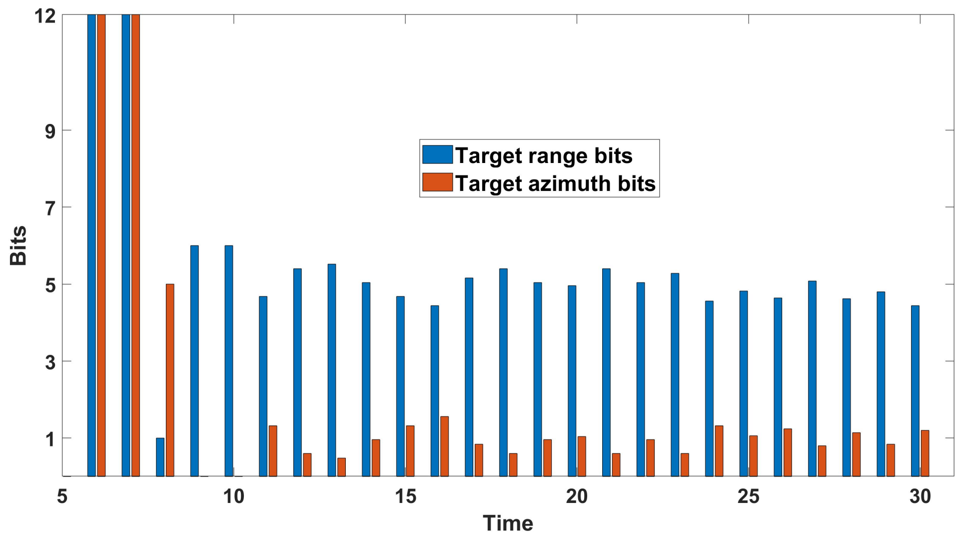


Figure 2.6: Bit allocation between Range and Azimuth

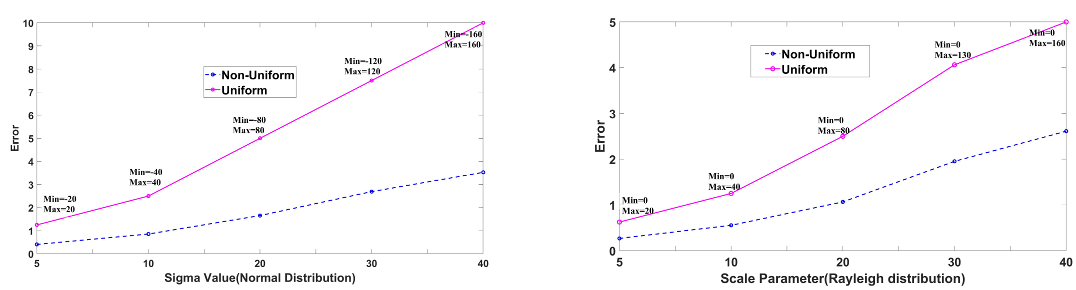


Figure 2.7: Comparison of Uniform and Non-Uniform Quantization for a Gaussian and Rayleigh distributed variable

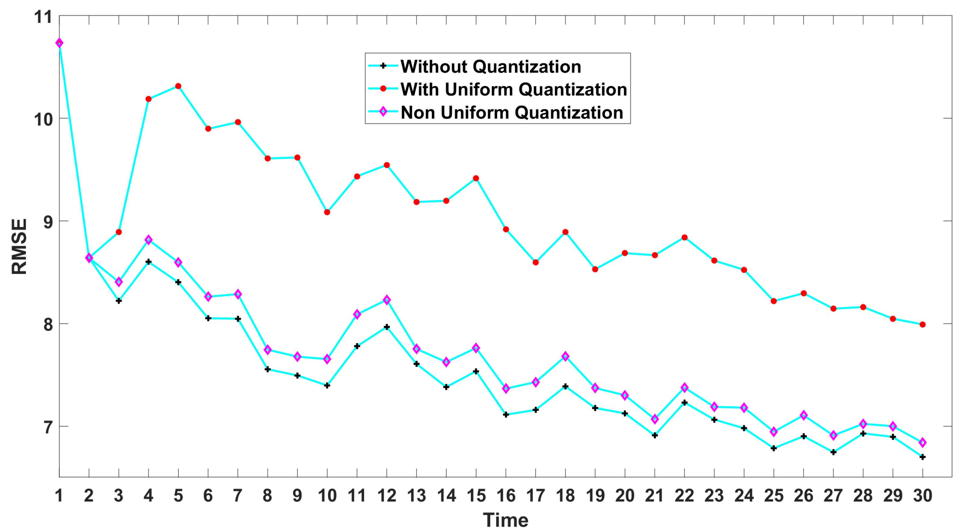


Figure 2.8: Comparison of RMSE using fixed bit uniform and Non-uniform Distribution

two sensors for the given target using the dynamic distribution of available bits. Fig.2.9, shows the trajectory of a track that is moving away from the sensors. In fixed allocation, six bits are allocated to each sensor. In dynamic allocation, two sensors share a maximum of ten bits at the FC in an adaptable manner. The target using the proposed allocation has a much lower RMSE when compared to the fixed bit allocation, as shown in Fig.2.10. In Fig.2.11, we show the distribution of bits between range and azimuth for the target, and the dynamic algorithm allocated more bits to azimuth than range based on its trajectory. Range and azimuth bits are the contributions of both sensors. In Fig.2.12, we show the distribution of the bits for range and azimuth for sensor1 and sensor2. As sensor1 performs better in terms of range than sensor2, a greater number of bits are assigned to it. The azimuth measurement is being increased by sensor2's improved azimuth performance.

- Number of Sensors: 2
- Number of Targets: 1
- Bandwidth available at FC (in bits): 10
- Bandwidth available at each sensor: 6
- Sensor1 range error: 5
- Sensor2 range error: 10
- Sensor1 azimuth error: 0.01
- Sensor2 azimuth error: 0.007

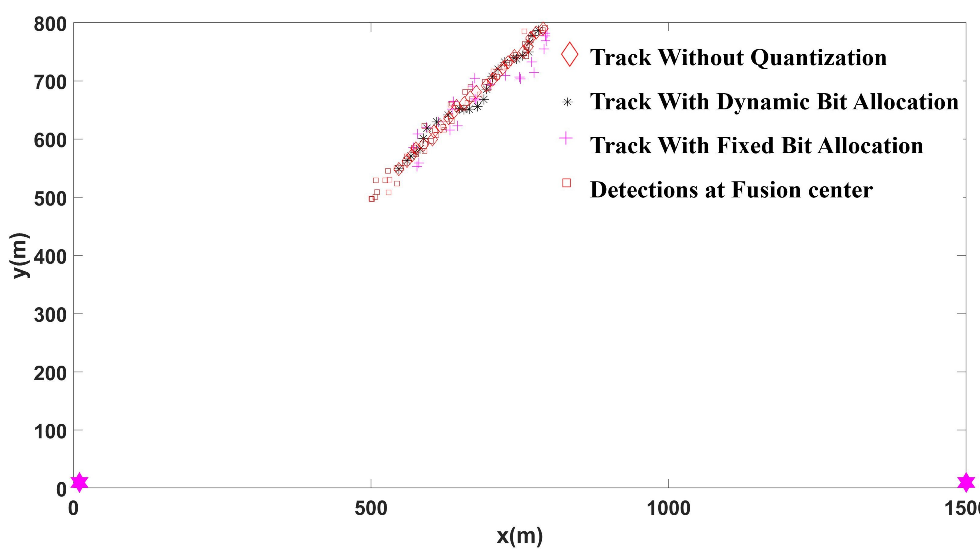


Figure 2.9: Target Trajectory with two sensors and one Target

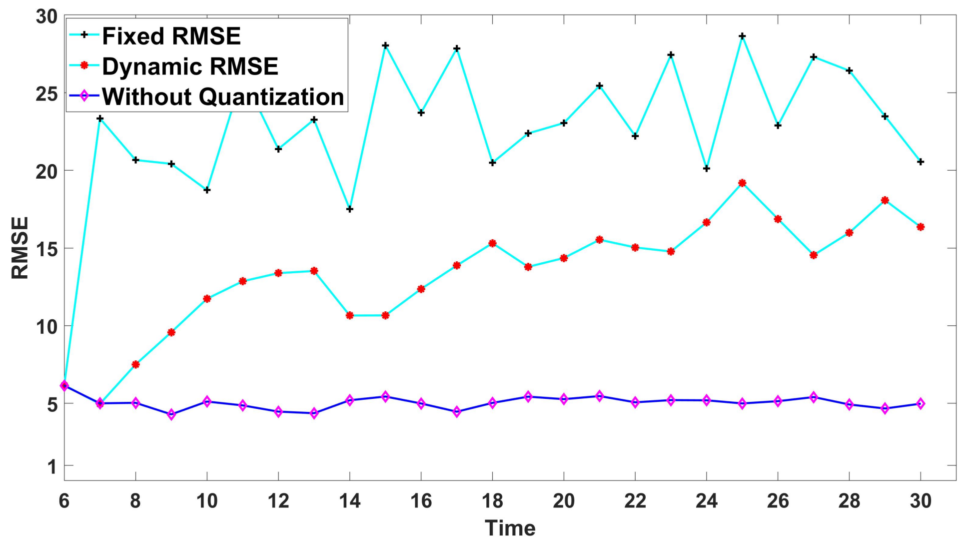


Figure 2.10: Comparison of RMSE using Dynamic bit allocation, Fixed bit Allocation(each sensor 6 bits), Without Quantization

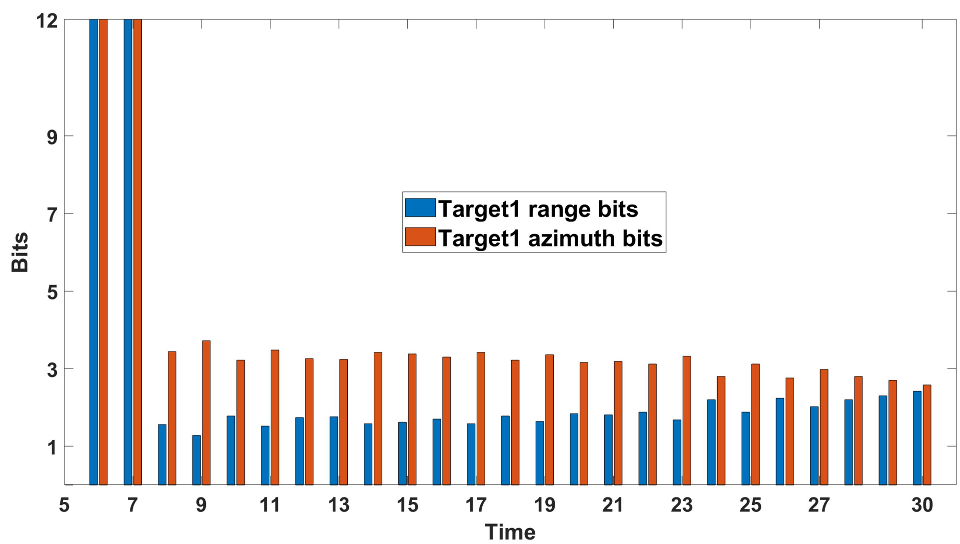
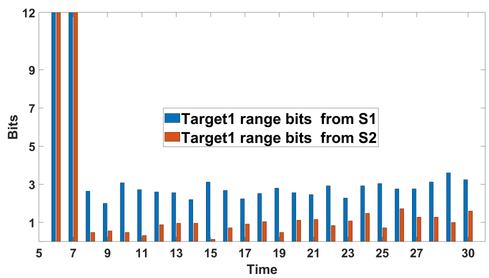


Figure 2.11: Distribution of bits between range and azimuth for Target1



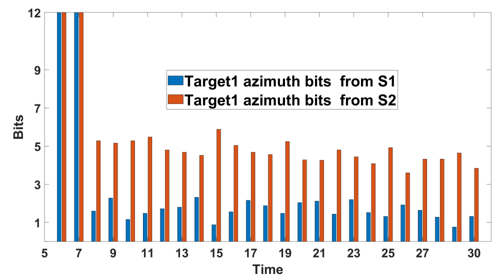


Figure 2.12: Distribution of bits between S1 and S2 for range and azimuth

2.6.3 Case 3:

In this experiment, we have four sensors and four targets. The results show the effective distribution of bits among the sensors and the targets using the dynamic distribution of available bits. Fig.2.13 shows the trajectories of four tracks that are in the tracking region of all four sensors. In Fig.2.14, we examined the RMSE with fixed, dynamic, and without quantization and found that adopting dynamic bit allocation significantly reduces RMSE for all four targets when compared to fixed allocation. In Fig.2.15, we compared the bits allocated to range and azimuth for target1 from all contributing sensors, and the dynamic bit allocation algorithm allocated an almost equal number of bits for range and azimuth. The four sensors each contribute a different number of bits at each scan period, which we compared in Fig.2.16 for the range for Target1. We demonstrate the reallocation of bits as a result of a mis-detection at the sensor node in Fig.2.17, using a local optimization problem. On the X-axis, we displayed the re-allocation of one target at a given time at any sensor. Following re-allocation, FC's bit allotment for a certain target either stays the same or grows. For instance, FC assigned 8 and 12 bits, respectively, for range and azimuth for a specific target at time 2. The sensor node redistributed the range and azimuth bits, allocating them to 12 and 16 bits, respectively. Additionally, the local bit distribution can be turned on or off. Through the use of a local optimization problem at each sensor node that optimizes the local fisher information, extra available bits resulting from mis-detections are distributed to existing tracks at the sensor node.

- Number of Sensors: 4
- Number of Targets: 4
- Bandwidth available at FC (in bits):100
- Bandwidth available at each Sensor:24

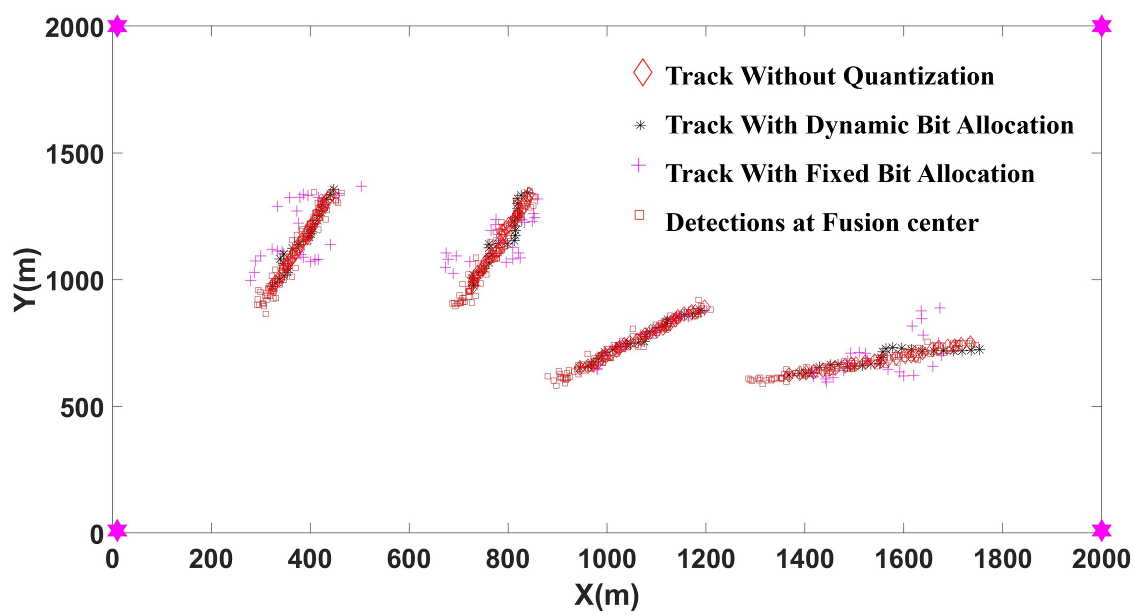


Figure 2.13: Trajectory-4 sensors and 4 targets

Figure 2.14: Comparison of RMSE

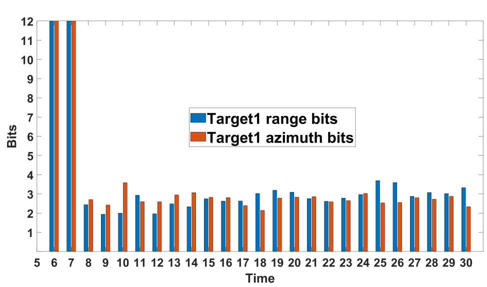


Figure 2.15: Range and azimuth bit allocation for Target1

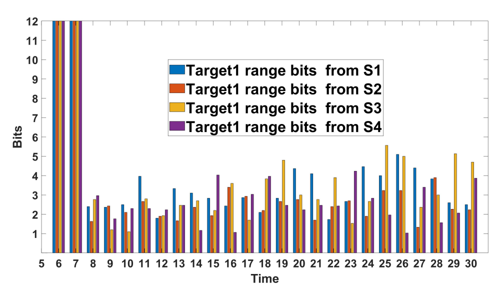


Figure 2.16: Target1 bit allocation for range from all sensors

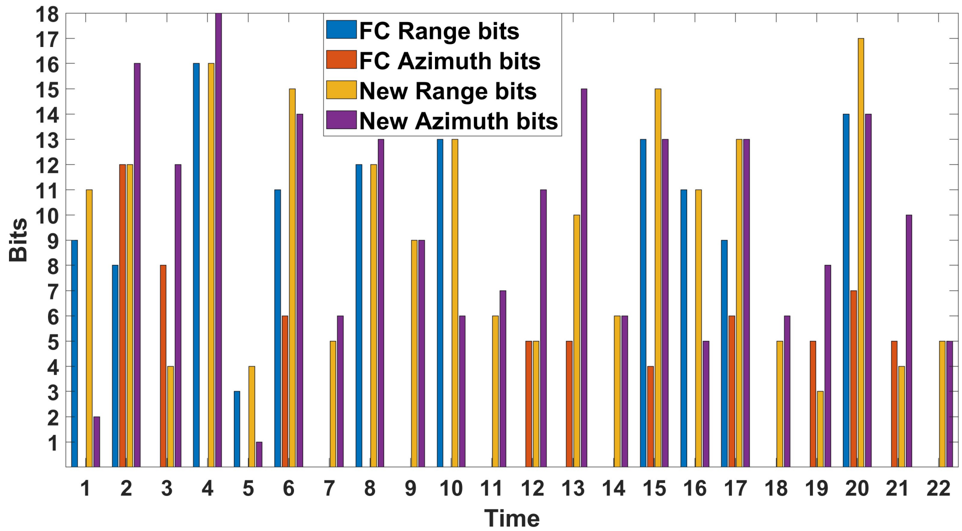


Figure 2.17: Re-allocation of bits due to mis-detections

2.6.4 Case 4 :

The fundamental idea behind bit allocation problems is to strike a balance between performance and the number of allocated bits. In essence, the more bits allocated, the higher the performance that will be attained, but the bandwidth consumption will also increase, and vice versa. The performance metric is the estimation error, the mean square error (MSE). This scenario is being used to demonstrate how the RMSE varies with bit allotment. As we give the targets more bits, the RMSE goes down. In this experiment, we compare the RMSE, as shown in Fig.2.18 using different available bits at the sensor node for a single target. As the number of available bits at the sensor node increases, RMSE decreases. Using this experiment, we analyzed the effect of available bits at the sensor node or at the FC on RMSE. We can also determine the number of bits required to achieve particular RMSE values for the given scenario.

Specifically, if we use the available bits effectively, fairly good performance can be achieved with a minimal number of bits.

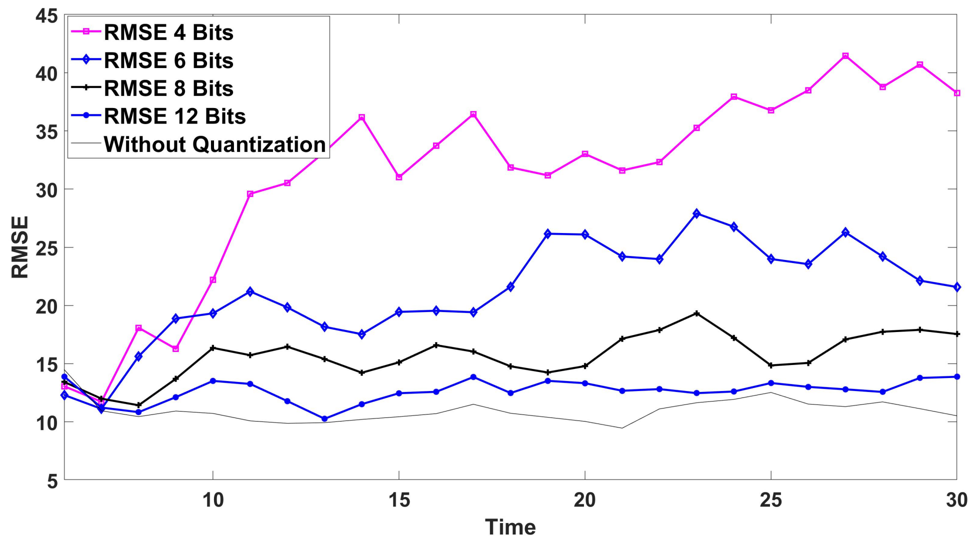


Figure 2.18: RMSE Comparison with different available bits at the sensor node

2.6.5 Case 5 :

In this case, we evaluated the effectiveness of the suggested approximate approach and contrasted the outcomes with the solution of the multi-objective integer problem obtained using the Genetic Algorithm(GA) that is implemented in MATLAB. The results demonstrate that the approximate algorithm's RMSE performance is highly comparable to GA and that its computing time is notably small. Table 4.2 shows the time required for the bit allocation using GA, as well as the proposed approximate algorithm for four sensors and four targets for each scan. The time is measured using *timeit* function in MATLAB over 100 trials. We compared the RMSE using GA and the proposed approximate approach using 4 sensors and 4 targets in Fig.2.19, and the performance of the suggested approximate technique is closer to GA. The default parameters in MATLAB are used for GA.

Table 2.1: Time Comparison of Genetic Algorithm(GA) Algorithm and Proposed Approximate Algorithm in seconds

Targets	**GA**	**Approximate**
2	3.8330	0.0027
4	4.6516	0.0058
8	6.0458	0.0083
16	6.9938	0.0104

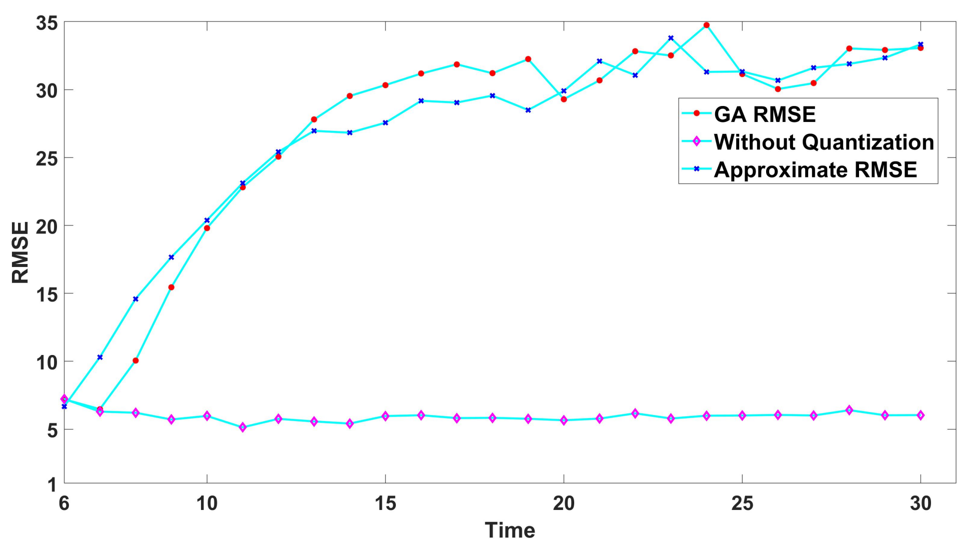


Figure 2.19: GA and Approximate Algorithm RMSE Comparison

2.7 Conclusion

In this chapter, the dynamic bit allocation problem for multi-target tracking is considered. Under bandwidth and energy constraints, the problem is formulated as a multi-objective integer optimization problem that minimizes the PCRLB and maximizes resource usage. Our approach distributes the bits for each target and also within the measurement vector by considering the target trajectory and sensor characteristics. We prioritized the tracks in SROI for fast initialization by considering tentative tracks. The issue was split into two optimization problems. By taking into account the available bits at the FC and each sensor node, the initial optimization problem is at the FC to distribute the bits to all tracks based on PCRLB. We also addressed the situation in which FC lacked knowledge about the number of new tracks and tentative tracks. The second optimization problem is at the local sensor node to handle mis-detections and re-allocate the extra available bits to tracks that optimize the fisher information. The simulation results demonstrate that even with a limited number of bits available, a combination of dynamic bit allocation and non-uniform quantization provides good tracking performance. We proposed an approximate algorithm that computes the priority and weight of each track based on the contribution of FI using static bit allocation. Simulation results show the effectiveness of the proposed algorithms versus fixed or static bit allocation. Experimental results show that the performance of the proposed approximate algorithm is close to GA implemented in MATLAB, and computation time is significantly low.

Chapter 3

Joint Bandwidth Allocation and Assignment of targets to Fusion Centers for Distributed Multi-Target Tracking

3.1 Introduction

Ground data gathering is quite challenging to do in particular types of situations, such as distant areas, deep forests, and severely cold locations. To collect the data, UAVs can be used as a mobile data collector, and the ground-based data can be collected through air traffic. Data collection is the basic function of a wireless sensor network (WSN) and is also an important research topic. There are several ways to collect the data from the deployed sensor networks; however, aerial data collection based on controllable Unmanned Aerial Vehicles (UAVs) have more advantages. It is free from mobility limitations and can be used where humans can not approach the location.

Nowadays, the use of unmanned aerial vehicles (UAVs) that can be used as flying base stations is seen as a promising approach to improve the coverage and performance of wireless networks in different scenarios, such as temporary hotspots and emergency situations. For example, mobile UAVs can establish efficient communication links to deliver messages to ground users, such as sensors. In fact, using UAVs as aerial base stations has many advantages. Importantly, due to their higher altitude, aerial base stations have a higher chance of providing line-of-sight (LOS) links to ground users. Also, UAVs can be easily moved around, which provides complete flexibility in how and where they can be deployed. They can provide high-speed, on-demand communications. Flying base stations can be deployed quickly on demand[77]. This is especially appealing for application scenarios, such as sudden or unpredicted events, emergency response, and search and rescue. Because of their high altitude above the ground, flying base stations are more likely to have a LoS connection with their ground users compared to their terrestrial counterparts, thus providing more reliable links for communication as well as multiuser scheduling and resource allocation[7]. As a consequence of the controllable high mobility of UAVs, flying base stations provides an additional degree of freedom (DoF) for communication performance enhancement, by dynamically adjusting their locations in 3-D to cater to the terrestrial communication demands. The above-listed uses make UAV-assisted communication an emerging new technology to support the ever-increasing and highly dynamic wireless data traffic in the future. In many Internet of Things (IoT) applications, a network of sensors that are wirelessly connected is vital because it provides a better picture of remotely sensed environments[84, 86].

However, conventional network data collection takes a high amount of energy because of the large number of data packets that need to be communicated on a hop-by-hop basis to the base station. To alleviate this problem, UAVs have been used to travel over the sensed environment to collect data. The flight time duration of a UAV depends on many factors, such as energy sources like the battery or the fuel type, weight, speed, and trajectory of the UAV. Optimal usage of UAVs and the distribution of resources are important components for the collection of data from wireless sensors. The performance and operational duration of the UAV system is fundamentally constrained by the limited onboard energy[3]. Although technologies have advanced dramatically over the past few decades, limited energy availability still severely hampers UAV endurance[12]. To address this problem, energy-efficient operations through smart energy management is required, that is, accomplishing missions with minimum energy consumption[80].

In this paper, we address the problem of energy-aware association and bandwidth distribution to the given targets in the area of interest (AOI) to maximize the tracking performance as well as utilize the limited available energy effectively. We propose a novel method of associating targets to fusion centers and efficiently assigning the available bandwidth to targets to improve tracking performance and prolong the usage time of each of the fusion centers as well as sensor nodes through optimal energy usage. Our important objective is to find an energy-efficient and energy-aware solution to the problem of pairing the targets with the fusion centers. The main applications of this work include the military field and environmental monitoring. The aim is to minimize the maximum energy consumption of all sensor nodes and fusion centers while ensuring that the required amount of data is collected reliably from each sensor node to get good tracking performance. The design is formulated as a multi-objective integer optimization problem[35].

This paper is organized as follows. In Section 3.2, we present an overview of related works and listed our main contributions. In Section 3.3, we present the system model, problem formulation, and model assumptions, as well as the relocation of fusion centers. We discuss and present the algorithm to initialize values for the genetic algorithm in Section 3.4. Details of two approximate algorithms are discussed in Section 3.5. We present the simulation results in Section 3.6, validating our model and analytical derivations. We finally conclude this paper in Section 3.7.

3.2 State of the art

In [54, 50, 52], the authors proposed a novel framework for efficiently deploying and moving UAVs to collect data in the uplink from ground-based IoT devices. In particular, they have determined the jointly optimal UAVs' locations, device associations, and uplink power control of the IoT devices, so that the total amount of transmit power of the devices is minimized under their SINR constraints. In addition, they have investigated the effective movement of the UAVs to collect the IoT data in a time-varying IoT network. In [21], the path planning problem for a single UAV is studied with the proposal of novel evolutionary operators: pull-to-desired-region (PTDR), push-from-forbidden-region (PFFR), and pull-to-final-point (PTFP). In addition to these newly proposed operators, standard mutation and crossover operators are used. In [85], the authors addressed the trajectory design problem for a UAV-enabled multicasting system. The UAV mission's completion time is minimized while ensuring that each GT is able to successfully recover the file with a given probability. A novel design for energy-efficient data collection in UAV-enabled WSNs was proposed in [87]. The sensor nodes (SN) wake-up schedule and UAV's trajectory are jointly optimized to minimize the maximum energy consumption of all SNs while making sure of reliable data collection in fading communication channels. With the successive convex optimization technique, an efficient iterative algorithm is proposed to find a suboptimal solution.

In [28], two power allocation schemes have been developed to support resource-aware design for target localization in distributed multiple-radar systems. One of these schemes minimize the total radiating power to accomplish a predetermined localization MSE threshold, while the other minimizes the achievable localization MSE for a given total energy budget. A closed-form expression for the CRB has been used to represent the localization MSE. The resulting power allocation non-convex optimization problem has been solved through both relaxation and domain decomposition methods, using Lagrange multipliers and the Karush-Kuhn-Tucker (KKT) conditions. In [73], the problems of joint path planning and sensor subset selection for multi-target tracking with multi-static sensor networks were considered. The problem was to select an optimal subset of the receivers and find the optimal path of the mobile transmitters so as to maximize the tracking performance of the time-varying number of targets. The problem is formulated based on the multi-target PCRLB by considering all the physical constraints.

In[38], the authors studied the UAVs assisted data collection in WSN. The working time of the UAV and the per-node capacity of WSN are derived for the scenarios of multiple UAVs and a single UAV. UAVs-supported data collection for WSN was studied. Firstly, the entire region is divided into multiple cells. Secondly, the flight paths for a single UAV and multiple UAVs are designed to cover all cells. The capacity of each of the sensors is derived, which is a the function of the number of sensors, the energy capacity of the UAV, the number of cells, and the height of the UAV. It was found that the per-node capacity using multiple UAVs is much greater than that with a single UAV. Then the optimal number of cells is derived to maximize the per-node capacity of WSN.

In [74], an optimization-based sensor management algorithm was considered for multi-target tracking under distributed architecture. The problem was to select subsets of sensors, assign them to LFCs, and assign the transmission power and frequency to each of the active sensors for the purpose of maximizing the tracking performance of multiple targets. The optimal formulation for the sensor management for the aforementioned problem was derived based on the PCRLB[72]. In [81], the authors investigated the problem of energy efficient computation and transmission resource allocation of federated learning over wireless communication networks and derived the energy and time consumption models for federated learning (FL) based on the rate of convergence. With these models, they have formulated a joint communication and learning problem to minimize the total transmission and computation energy of the network.

The paper, [82], considers a UAV-enabled WSN where a UAV is dispatched to collect data from multiple SNs with the objective of maximizing the minimum average data collection rate of all SNs under the possible UAV trajectory, reliability constraints, and communication scheduling. The notion of operating radars in groups, or clustering, has been introduced to multiple radar systems in [29]. Tools have been developed for the identification of optimal sets that minimize the number of radars that are active while guaranteeing the required estimation performance or minimize the estimation error, which is MSE for a predetermined set of sizes. Cost parameters have been introduced to integrate decision factors in the selection process. The selection problem has been defined as a KP and heuristic algorithms, based on a greedy strategy with multi-start local search, have been proposed. Three approximate solutions for the allocation of power or/and bandwidth are provided in [23] given that transmitters access the medium using disjoint bandwidths of the spectrum. Substantial simulations are run on the resource allocation performance for different SNR's in terms of the theoretical CRLB and verified by a multilateration algorithm. The best accuracy is achieved by jointly optimizing bandwidth allocation and power among the MIMO radar elements, the actual bandwidth is much more valuable resource than power.

In [51], the deployment of an unmanned aerial vehicle (UAV) as a flying base station used to provide wireless communications to a given region is analyzed. Specifically, the coexistence between the UAV, that is transmitting data in the downlink, and an under-laid device-to-device (D2D) in the communication network is considered. For this model, a tractable analytical framework for rate analysis and coverage is derived. Two scenarios are considered: a mobile UAV and a static UAV. In [88], a TAPA strategy has been put forward for multi-target tracking in multiple distributed MIMO radar networks in a cluttered environment. The optimization model has been established as minimizing the overall tracking performance subject to the power budget and the radar direction capability. Consequently, an efficient two-step-based technique has been developed for problem-solving. In [78], two important and limited system resources are considered for optimization: the transmitted power and the number of radar nodes. A joint node selection and power allocation (JSPA) strategy is developed with the goal of tracking multiple targets. The proposed mechanism implements the optimal resource allocation using the feedback information in the tracking recursion cycle for the purpose of improving the worst-case tracking accuracy with multiple targets.

In conclusion, the following are the key differences between the research done in the literature and the proposed work. To improve the robustness of the given system, a number of fusion centers are deployed to collect the data. We take into account the possibility that a sensor could be in a location that is shared by several fusion centers. Hence, the sensor is able to send some targets to one fusion center and other targets to different fusion centers using different frequency channels. Additionally, we also consider the case in which a target is being tracked by many sensors, and the information to be gathered from each sensor depends on the connectivity of the sensors with the fusion centers. Achieving the best targets to FCs assignment and bandwidth allocation to each target is a crucial goal of this work. We formulate the problem as a multi-objective integer optimization problem. Our algorithm consists of three steps. The first step is bandwidth allocation to targets at each of the sensors. In the second step, we relocate the fusion centers to the centroid location to optimize the communication cost. The judicious selection of FCs to move them closer to overloaded sensor nodes helps to lessen energy consumption and reduce communication costs.

This step is performed just before the targets to FCs assignment process based on the current bandwidth allocation. The main contributions are summarized as follows.

- In this work, we propose a novel strategy for joint bandwidth allocation and assignment of targets to fusion centers for multi-target tracking in multiple distributed radar networks against a cluttered background.
- We propose an algorithm for generating initial values for the multi-objective integer optimization problem.
- Two approximate bandwidth distribution algorithms for joint bandwidth allocation and target assignment are proposed, which provide nearly optimal results at less computational time.

3.3 System Model and problem formulation

Consider a set of sensor nodes distributed over a geographical area. Fusion centers are deployed to collect the data from these sensor nodes and communicate the tracks back to a single base station or a control center. Initially, we assume that we know the placement of fusion centers. At the beginning of each slot, we compute the association of the targets to FC and the bandwidth distribution to all the targets based on the locations of currently active devices that are assumed to be known to the control center. Hereinafter, the time instance at which the FCs' locations and associations are jointly updated, is referred to as the update time.

The update times are denoted by t_n. At each update time t_n, based on the location of active devices, the optimal FCs' locations, and the corresponding association must be determined for effectively serving the ground devices. In our model, we consider some specific time instances (update times) at which the FCs locations and target associations are optimized. In particular, considering the fact that the set of active devices and their load may continuously change, continuously updating the FCs' locations, the devices' transmit powers, and the targets to FCs associations may not be feasible as they can lead to low reliability, high FCs energy consumption, and a need to solve complex real-time optimization processes. Therefore, update intervals are determined by the tracking scenario, target characteristics like speed and manoeuvrability, and the availability of processing resources. In our representation, the update time is a design parameter that depends on the activation of the devices, the energy of FCs, and the target properties in the given scenario. For highly manoeuvrable targets, we may need to have a small t_n to get good performance. Given this model, our goal is to determine the best joint association of the targets to FCs and bandwidth allocation at each update time t_n in order to reduce the overall PCRLB while satisfying the bandwidth limits of each device.

In fact, the services that the sensor devices provide determine whether they are activated. For instance, in some applications such as weather monitoring, smart grids, and home automation, the sensor devices need to report their data periodically. However, the devices can have random activations in health monitoring or smart traffic control applications. Therefore, the FCs must be properly deployed to collect the sensor device data while dynamically adapting to the activation patterns of sensor devices. Naturally, the optimal locations of the FCs and their update times depend on the activation process of the sensor devices.

In our work, we considered mainly four constraints into account. The first is the bandwidth of the sensors, the second is the bandwidth of the fusion centers, and the third is the cost of communication, which depends on the distance between source and destination. Sensors are often powered by tiny batteries, which are typically non-rechargeable and are used in tracking applications. Due to bandwidth restrictions, we assume that each sensor only chooses one measurement for a target and quantizes the data before transmitting it to the fusion center. A fusion center can be a drone cell or UAV that has limited energy and wants to optimize the available energy. The fourth constraint is the number of frequency channels available for communication. For instance, if the number of frequency channels accessible is small, the sharing of targets among the FCs is constrained. Further, the following assumptions are made to simplify the problem.

Assumption 1: The number of fusion centers is fixed, and their initial placement locations are known.

Assumption 2: The fusion centers can move whenever required with maximum speed within a given time to the designated location.

Assumption 3: All the sensors are active at all times and can track the targets if they are within their tracking region.

Assumption 4: The number of targets may vary from time to time. Each sensor node selects only one measurement per target to send to the fusion center.

Assumption 5: Multiple sensors can track a single target.

Assumption 6: Each sensor can communicate with one or more fusion centers, however, information about each target is communicated to only one fusion center. If a sensor has multiple targets to communicate with, it can send different targets to different fusion centers so that the allocation gives better tracking performance.

3.3.1 Problem Formulation

Consider a system consisting of a set $\mathcal{L} = \{1, 2, ...L\}$ of L sensor devices. Examples of such devices include various types of sensors used for environmental monitoring, smart traffic control, and smart parking devices. In this system, a set $\mathcal{K} = \{1, 2, ..., K\}$ of K FCs' must be deployed to collect data from ground sensor devices. These FCs' can dynamically move when needed, to effectively serve the sensor devices using communication links. There is a total T number of targets at the control center consisting of a set $\mathcal{T} = \{1, 2, ...T\}$. There is a maximum available F number of frequency channels consisting of set $\mathcal{F} = \{1, 2, ...F\}$. The locations of device $i \in \mathcal{L}$ and FC $j \in \mathcal{K}$ are, respectively, given by (x_i, y_i) and (x_j, y_j, h_j). In our model, we consider a centralized network in which the locations of the devices and FCs are known to a control center located at a central cloud server. The control center will determine the FCs locations, the targets to FCs association, and the bit allocation to each target. At the beginning of each slot, the positions of the FCs, as well as the targets to FCs association, are updated based on the active devices and the number of targets that are assumed to be known to the control center. The sample scenario with three clusters with overlapping sensors is shown in Fig.3.1. Once the targets and FCs have been associated, each FC can assign bits to each target of each sensor using uniform or non-uniform quantization.

3.3.2 Objectives

The objective is to maximize the tracking performance of the system by optimally using the available resources. The tracking performance is measured by the accuracy of the existing targets' estimates. The problem is to allocate the targets to FCs and

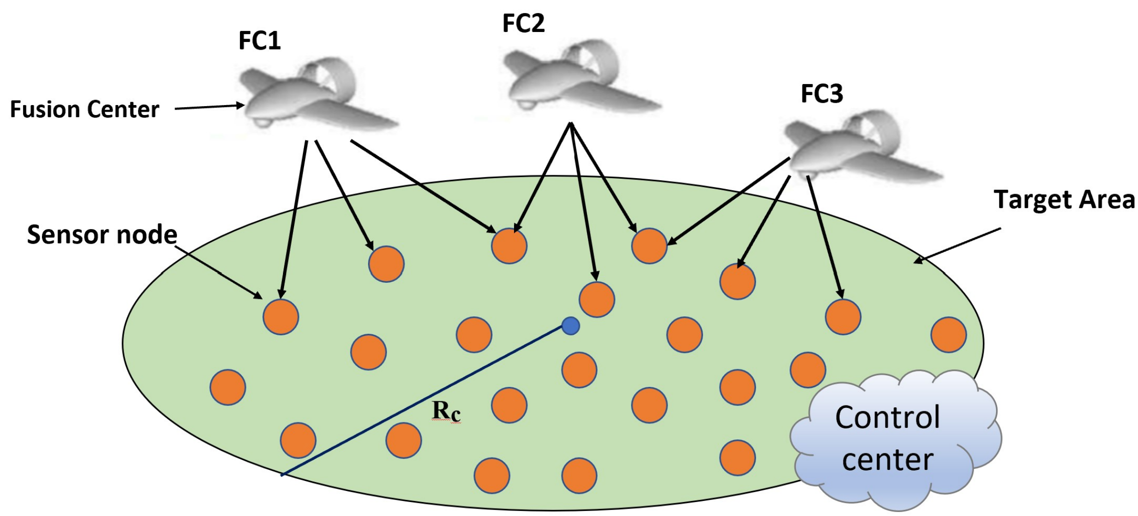


Figure 3.1: Sample Scenario representation

assign the transmitting frequency and bandwidth to each target in order to maximize the tracking performance. Each FC reports to the control center to get a global picture of the tracking region. Each sensor in this design is permitted to be associated with one or more FCs, but each target at the sensor node is sent to only one FC in order to prevent information duplication.

Let A_{ijtf} be the indicator function that takes the value 1 if target t of sensor device i is assigned to FC j through frequency channel f and 0 otherwise. Then, the first objective is given by Eq.3.3.6.

$$E[\hat{x}_t - x_t][\hat{x}_t - x_t]^\top \geq J_t^{-1} \tag{3.3.1}$$

$$J_0 = {P_0}^{-1} \tag{3.3.2}$$

$$J_{prior} = (Q_{k-1} + F_{k-1}J(k-1)^{-1}F_{k-1}^{\top})^{-1} \tag{3.3.3}$$

$$J(k)^{-1} = (J_{prior} + \sum_{i=1}^{L} \alpha H_{i,k}^{\top} R_i^{-1} H_{i,k})^{-1} \tag{3.3.4}$$

$$\alpha = \sum_{j=1}^{K} \sum_{f=1}^{F} A_{ijtf} \tag{3.3.5}$$

$$min \sum_{t=1}^{T} W_1 * \det(E[\hat{x}_t - x_t][\hat{x}_t - x_t]^{\top}) \tag{3.3.6}$$

- J_0 is the initial Fisher Information (FI).
- P_0 is the initial error covariance matrix.
- J_{prior} Prior FI.
- $J(k)$ is FI of a target at time k.
- J_t is FI of target t.

The second objective is to maximize the reward for each fusion center that uses less bandwidth. The total allocated bandwidth of all fusion centers should be minimized. B_{ijf}^t is the bandwidth allocated by FC j to target t at the sensor node i using frequency channel f. In other words, to maximize the energy available at each FC, it is given by

$$\min \left\{ \sum_{i=1}^{L} \sum_{t=1}^{T} \sum_{f=1}^{F} W_2 * A_{ijtf} * B_{ijf}^t \right\} \quad \forall j \in \mathcal{K} \tag{3.3.7}$$

The third objective is to maximize the reward for each sensor device that uses less bandwidth. The total allocated bandwidth of all sensor nodes should be minimized. In other words, to maximize the energy available at each sensor node B_i, it is given by

- i is the index for sensor devices, and L is the total number of sensors.
- j is the index for FCs, and K is the total number of FCs.
- t is the index for targets, and T is the total number of targets.
- f is the index for frequency channels, and F is the total frequency channels.

$$\min \left\{ \sum_{j=1}^{K} \sum_{t=1}^{T} \sum_{f=1}^{F} W_3 * A_{ijtf} * B_{ijf}^{t} \right\} \quad \forall i \in \mathcal{L} \tag{3.3.8}$$

Reducing the number of frequency channels that sensors employ to communicate with FCs is the fourth goal. If a sensor is connected to more than one FC, it can be given more than one frequency channel. For instance, we require two frequency channels to transmit the data to the FCs if a sensor node has two targets, each of which is assigned to a different fusion center.

$$\min \left\{ \sum_{f=1}^{F} W_4 * A_{ijtf} \right\} \quad \forall i \in \mathcal{L} \qquad \forall j \in \mathcal{K} \qquad \forall t \in \mathcal{T} \tag{3.3.9}$$

The fifth objective is to minimize the cost of communication between the sensor nodes and FC.

$$\min \sum_{i=1}^{L} \sum_{j=1}^{K} \sum_{t=1}^{T} \sum_{f=1}^{F} W_5 * A_{ijtf} * B_{ijf}^{t} * E_{ij} \tag{3.3.10}$$

The energy consumed in transmitting a one-bit size over a transmission distance d_{ij}, E_{ij} is defined as

$$E_{ij} = (E_{elec} + \varepsilon_{Amp} d_{ij}^{\lambda}) \tag{3.3.11}$$

where

- E_{elec} is electronic energy.
- ε_{Amp} transmitter amplifier.
- λ path-loss component $(2 \leq \lambda \leq 4)$.
- d_{ij} is the distance between sensor device i and FC j.
- E_{ij} is the energy consumed for transmitting a single bit from the sensor device i to FC j.

The sixth objective is to reduce the time it takes to communicate the data from the fusion centers to the control center. The control center should receive the data that the FCs have collected. The network of FCs should always be connected to the control center in a multi-hop fashion, since the distance between the FCs and the control center may be greater than the communication range of an FC. It is dependent on two elements. The first one is each fusion center's data transmission rate and data capacity. Let λ_i be the data rate of the fusion center i and D_i is the data it has to communicate to the control center.

$$\min \sum_{j=1}^{K} W_6 * \frac{D_j}{\lambda_j} \tag{3.3.12}$$

Depending on the problem, we can give weight to each of these objectives[71]. The final single objective function is a summation of all five objectives, with some weight assigned to W1, W2, W3, W4, W5, and W6. The sum of all the weights should be equal to 1.

$$Eq3.3.6 + Eq3.3.7 + Eq3.3.8 + Eq3.3.9 + Eq3.3.10 + Eq3.3.12 \tag{3.3.13}$$

$$W1 + W2 + W3 + W4 + W5 + W6 = 1 \tag{3.3.14}$$

3.3.3 Constraints

Bandwidth at FC

The first constraint is to make sure that each FC does not utilize more bandwidth than is actually available. B_j is bandwidth available at FC j.

$$\sum_{i=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} * B_{ijf}^{t} \leq B_j \quad \forall j \in \mathcal{K} \tag{3.3.15}$$

Bandwidth at sensor device

The second is to make sure that no sensor device's maximum bandwidth usage exceeds the bandwidth that is really available. B_i is the bandwidth available at sensor node i.

$$\sum_{j=1}^{K}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} * B_{ijf}^{t} \leq B_i \quad \forall i \in \mathcal{L} \tag{3.3.16}$$

Target Assignment

The third one is to make sure one target is assigned to only one FC.

$$\sum_{i=1}^{L}\sum_{j=1}^{K}\sum_{f=1}^{F} A_{ijtf} \leq 1 \quad \forall t \in \mathcal{T} \tag{3.3.17}$$

Frequency channel Assignment

The fourth one is to restrict each target to being associated with only one of the frequency channels. A sensor can have one or more frequency channels associated with it.

$$\sum_{f=1}^{F} A_{ijtf} \leq 1 \quad \forall i \in \mathcal{L} \quad \forall j \in \mathcal{K} \quad \forall t \in \mathcal{T} \tag{3.3.18}$$

When a target is being monitored by two separate sensors, it is possible to assign it two frequencies.

Sharing of Frequency Channel

The fifth is to ensure that a frequency channel can be shared by all of a sensor's targets that are allocated to a single FC. For example, s1 is associated with FC2, and 3 targets are assigned to FC2, using frequency channel number 10. For $i = 1, \quad j = 2, \quad f = 10,$ then $\sum_{t=1}^{T} A_{ijtf} = 3$. If n_i is the total number of targets at s_i then

$$0 \leq \sum_{t=1}^{T} A_{ijtf} \leq n_i \quad \forall i \in \mathcal{L} \quad \forall j \in \mathcal{K} \quad \forall f \in \mathcal{F} \tag{3.3.19}$$

Number of sensor devices each FC can associate

The sixth constraint is to limit the number of sensors that can be assigned to one FC. Due to physical limitations, each FC can not handle more than n_i sensor devices for a given FC j

$$\sum_{i=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} \leq n_i \quad \forall j \in \mathcal{K} \quad (20) \tag{3.3.20}$$

Distance

The seventh constraint is the distance between sensor device i and FC j, d_{ij} cannot be more than γ_j.

- The maximum radius of an FC j is r_j.
- γ_j can be derived using height and the maximum radius of FC j.
- θ_B is the beam width of the antenna of FC.
- h is the height of FC from the ground, as shown in Fig.3.2.

$$A_{ijtf} * d_{ij} \leq \gamma_j \quad \forall i \in \mathcal{L} \quad \forall j \in \mathcal{K} \quad \forall f \in \mathcal{F} \quad \forall t \in \mathcal{T} \tag{3.3.21}$$

where

$$\gamma_j = \sqrt{h^2 + r_j^2} \tag{3.3.22}$$

$$r_j = h * \tan(\theta_{\mathrm{B}}/2) \tag{3.3.23}$$

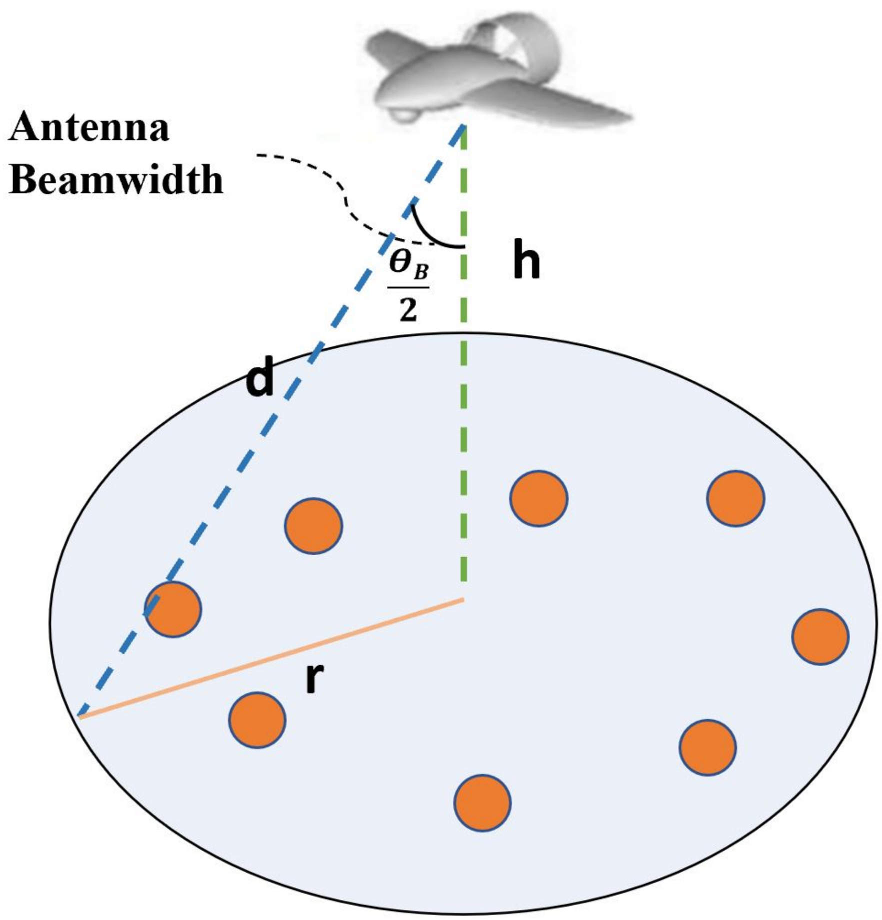


Figure 3.2: Placement of fusion center

Sensor Coverage

Each sensor must be within at least one FC's coverage area.

$$\sum_{j=1}^{K}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} \geq 1 \quad \forall i \in \mathcal{L} \tag{3.3.24}$$

3.3.4 Relocation of fusion centers

To communicate efficiently with the assigned sensor nodes, FC is relocated to the optimum location based on the locations of the assigned sensors and the amount of data they send. Since the energy consumed is directly proportional to the distance between the data source and destination, it is more energy-efficient if the fusion center is closer to the sensor node, which sends a large amount of data. The new positions for fusion centers shall be computed based on the bandwidth allocation at the previous update time, the location of sensor nodes, and the fusion centers. By taking into account the bits allotted to each of the sensor nodes within its coverage, a fusion center is moved to the centroid of the location of the sensors. Each sensor location (x_i, y_i) is assigned a weight, which is calculated using the bandwidth allocated to it. If (x_j, y_j, h_j) optimal location of FC j by keeping the same height as in the previous update time is given as

$$x_j = \frac{\sum_{i=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} * B_{ijf}^{t} * x_i}{\sum_{i=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} * B_{ijf}^{t}} \qquad \forall j \in \mathcal{K} \tag{3.3.25}$$

$$y_j = \frac{\sum_{i=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} * B_{ijf}^{t} * y_i}{\sum_{i=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{F} A_{ijtf} * B_{ijf}^{t}} \qquad \forall j \in \mathcal{K} \tag{3.3.26}$$

3.4 Create the initial population

Due to the probabilistic nature of several steps in the genetic algorithm, the initial population plays an important role in finding the optimal solution. If initial values are in proximity to the optimal solution, even with fewer iterations, the algorithm quickly converges to the optimal solution. It takes several runs to get the best fitness value. It is important to choose the most suitable initial values for solving the optimization problem. As the CRLB of each target decreases by assigning more bits, each target tries to get the maximum number of bits. This simple concept is used to initialize the values that can be solved in linear time. For the initialization algorithm, we do not need complete data about each target at the control center. It is sufficient to have the number of targets that can be associated with each fusion center and the available bandwidth at each of the fusion center and sensor nodes. First, we form an assignment matrix with rows as targets and fusion centers as columns. We compute the total number of targets that can be assigned to each fusion center. Initially, the available bandwidth is equally divided among the eligible targets. The value at the i row and j column is the equally divided bandwidth of j FC. The detailed initialization algorithm is given in Algorithm 2.

Algorithm 2 Create Initial Population

Require: Let T be the number of tracks at all sensors, and K is the number of fusion centers with the given available bandwidth.

Ensure: Bandwidth distribution for all tracks, returns the matrix of size $T \times K$.

1: Compute the initial assignment matrix, A, by dividing the available bandwidth equally among the eligible targets. Each row i represents a target, and a column j represents each FC. If B_j is bandwidth available at the FC j and eligible targets to be assigned to the FC are n then...

2: Find the maximum element in the assignment matrix $\arg\max A$. Let $[I\_row, J\_col]$ be the index of the maximum element. It means target at I_row is associated to fusion center J_col.

3: Make all the other elements of I_row as zero by distributing the bandwidth to other non-zero elements in the same column. This is to ensure that the target is assigned to only one fusion center.

4: Repeat steps 2 and 3 for T times.

5: Identify the largest non-zero element in each row, if any; this entry will serve as the bandwidth designated for the specified target.

3.4.1 Example

For the given Fig.3.3, where we have three FCs, three sensors, and six targets. The bandwidths at FC1, FC2, and FC3 are 32, 6, and 6, respectively. The initial assignment matrix A is as follows according to Step1 from Algorithm 2.

$$\mathbf{A} = \begin{array}{c c} & \begin{array}{ccc} FC1 & FC2 & FC3 \end{array} \\ \begin{array}{c} t1 \\ t2 \\ t3 \\ t4 \\ t5 \\ t6 \end{array} & \begin{bmatrix} 8 & 2 & 0 \\ 8 & 1 & 0 \\ 8 & 1 & 0 \\ 0 & 1 & 2 \\ 0 & 1 & 2 \\ 8 & 0 & 2 \end{bmatrix} \end{array}$$

After the first two iterations the matrix, A looks as follows.

$$\mathbf{A} = \begin{array}{c} \\ t1 \\ t2 \\ t3 \\ t4 \\ t5 \\ t6 \end{array} \begin{array}{c} \begin{array}{ccc} FC1 & FC2 & FC3 \end{array} \\ \begin{bmatrix} 8 & 0 & 0 \\ 8 & 0 & 0 \\ 8 & 2 & 0 \\ 0 & 2 & 2 \\ 0 & 2 & 2 \\ 8 & 0 & 2 \end{bmatrix} \end{array}$$

The final matrix after the completion of the algorithm is as follows.

$$\mathbf{A} = \begin{array}{c} \\ t1 \\ t2 \\ t3 \\ t4 \\ t5 \\ t6 \end{array} \begin{array}{c} \begin{array}{ccc} FC1 & FC2 & FC3 \end{array} \\ \begin{bmatrix} 8 & 0 & 0 \\ 8 & 0 & 0 \\ 8 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 6 \\ 8 & 0 & 0 \end{bmatrix} \end{array}$$

The final assignment is t1, t2, t3, and t4 to FC1, each 8 bits, t4 to FC2, and t5 to FC3 each 6 bits.

3.5 Solution Techniques

This section introduces two suboptimal approximate algorithms for allocating the targets to the fusion centers. The first one is the approximate greedy bandwidth allocation algorithm, which will be proven to yield nearly optimal results while taking substantially less time to compute than solving a multi-objective optimization problem. The T targets at L numbers of sensors in the network must be allocated across the available K number of fusion centers that have a specific amount of bandwidth at each time step of tracking for the following time step. Keep in mind that the Fisher information matrix $J(k)$ of a target as given in Eq.3.3.4 is from all the contributing sensors. If more than one sensor contributes to a target's information, we calculate each sensor's individual contribution to determine the bits that should be assigned to each contributing sensor. The Fisher information can be maximized by maximizing its determinant while taking the bandwidth constraint into consideration in the formulation of an approximate greedy bandwidth allocation for tracking applications. We examine the computational complexity of the greedy approximate algorithm, in terms of the number of matrix summations. Algorithm 3 provides a comprehensive algorithm. For a single FC, with bandwidth, B, and with T targets, we need at most $T(2B-1)$ matrix summations, and the details are given in [46]. So for K number of FCs, we require $KT(2B-1)$ number of matrix additions. If FCs have different bandwidths, then B is the maximum of all the bandwidths. w_i is the weight given to each target. Based on each target's importance, we can assign a different weight in a number of different ways. To give the targets that are near to FC priority, the weight may also be computed based on how far the target is from FC. The second approximate algorithm starts with the initial assignment of the matrix derived from

Algorithm 3 Approximate Greedy Bandwidth Distribution Algorithm

Require: Let T be the number of tracks at all sensors, and K is the number of fusion centers with the given available bandwidth.

Ensure: Bandwidth distribution for all tracks using the greedy algorithm.

1: Compute assignment matrix using Algorithm 2.
2: **for** `i=1:`K **do**
3:   Let n be the number of tracks with non-zero entries in the matrix from step 1, and B_i is the bandwidth for FC_i.
4:   Set $b_0 = [b_1 = 0, b_2 = 0, ..., b_n = 0]$
5:   **for** `k=1:`B_i **do**
6:     **for** `j=1:n` **do**
7:       To the target, j add one bit and compute FI of the target, $w_j \det(J(b_j+1))$.
8:     **end for**
9:     Find the target t^* for which FI is maximum.
10:     $t^* = \arg\max_j w_j \det(J(b_j + 1))$
11:     Update $b_t^* = b_t^* + 1$
12:     Update $b_k = [b_1, ..., b_t^*, ..., b_n]$
13:   **end for**
14: **end for**

Algorithm 2, where it assigns an equal number of bits to all possible targets. In light of bandwidth constraints, our goal is to identify the optimal bit assignment vector, which is a bit assignment for all the targets. After equally dividing the bits among the targets, the algorithm's aim is to change the bits so that the total Fisher information matrix is maximized. The fixed minimum increment in the FI that we anticipate is called threshold, denoted by ϵ. First, select the target that provides the least FI using one fewer bit than the original bits, and take one bit away from that target's bits. The next step is to identify a target that contributes the most FI by adding one bit to it. As long as the increase in the FI is more than the specified threshold, ϵ from the previous stage, repeat the reallocation. The comprehensive algorithm is provided under Algorithm 4.

Algorithm 4 Approximate Bandwidth Distribution Algorithm-2

Require: Let T be the number of tracks at all sensors, and K be the number of fusion centers with the given available bandwidth.

Ensure: Bandwidth distribution for all tracks using an approximate algorithm.

1: Compute the assignment matrix using Algorithm 2.
2: **for** `i=1:`K **do**
3:   Let n be the number of tracks with non-zero entries in the matrix from step 1, and B_i is the bandwidth for FC_i.
4:   Set $b = [b_1, b_2, ..., b_n]$ from the matrix from step 1.
5:   **repeat**
6:     **for** `j=1:n` **do**
7:       compute FI1 of the target j, $w_j \det(J(b_j))$.
8:     **end for**
9:     **for** `j=1:n` **do**
10:       compute FI2 of the target j, $w_j \det(J(b_j - 1))$.
11:     **end for**
12:     Find the target t^* for which (FI1-FI2) is minimum.
13:     $\text{diff}(t^*) = \arg\min_j w_j[\det(J(b_j)) - \det(J(b_j - 1))]$
14:     **for** `k=1:n` **do**
15:       **if** $k \neq t^*$ **then**
16:         compute FI3 of the target, $w_j \det(J(b_k + 1))$.
17:       **end if**
18:     **end for**
19:     Find the target t' for which (FI3-FI1) is maximum.
20:     $\text{diff}(t') = \arg\max_k w_k[\det(J(b_k + 1)) - \det(J(b_k))]$
21:     Compute $\Delta = \text{diff}(t') - \text{diff}(t^*)$
22:     **if** $\Delta \geq \epsilon$ and $t^* \neq t'$ **then**
23:       Update $b_{t^*} = b_{t^*} - 1$
24:       Update $b_{t'} = b_{t'} + 1$
25:       Update $b = [b_1, .., b_{t^*}, ..., b_{t'}, ..., b_n]$
26:     **else**
27:       return b vector.
28:     **end if**
29:   **until** $\Delta \geq \epsilon$
30: **end for**

3.6 Performance Analysis

Consider a simple example where three sensors, let's say S1, S2, and S3, are deployed in a triangle fashion. The sensors have different sensor characteristics with different bandwidths and energy availability. We have three fusion centers, FC1, FC2, and FC3, to collect the data from these three sensors. S1 has three targets; t1, t2, and t3. S2 has two targets, t4 and t5, and S6 has one target, t6. S1 is in the coverage of FC1, and FC2. S2 is in the coverage of FC2 and FC3. S3 is in the coverage of FC1 and FC2. The details are shown in Fig.3.3. In fixed allocation, S1 is allocated to the closest fusion center FC2, S2, and S3 are allocated to FC3 and FC1, respectively. All the targets at the given sensor are allocated to the given fusion center. The total available bits at FC1, FC2, and FC3 are 32, 6, and 6, respectively. Using the adaptive approach, we allocate the targets to fusion centers which minimizes the CRLB. We give equal weight to all the objective functions in all our simulations. Create the initial population. For t1 to t5, the RMSE of the adaptive approach is much better than that of fixed allocation. All the bandwidth at FC1 is assigned to t6 in a fixed allocation. However, in adaptive allocation, it is shared by the other three targets. So only t6 has a little better RMSE performance using fixed allocation than adaptive allocation. In Fig.3.4, and Fig.3.5, we compared the RMSE results of all 6 targets using fixed allocation and adaptive allocation of targets to fusion centers.

In Fig.3.6, we compared the CRLB fitness function value using randomly generated initial values and the calculated initial values using the proposed algorithm. With the given number of iterations, the genetic algorithm with calculated initial values always gives better fitness values than the one with randomly generated initial values. In the next scenario, we have three targets. Each target is tracked by two sensor nodes,

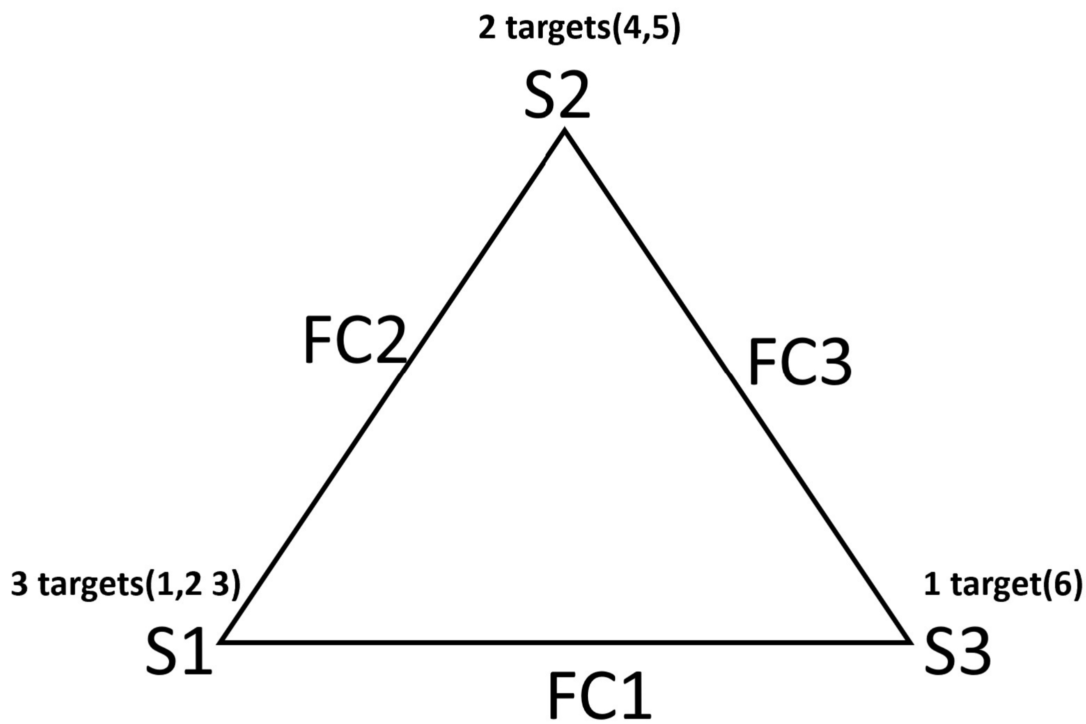


Figure 3.3: Simulation Scenario-I

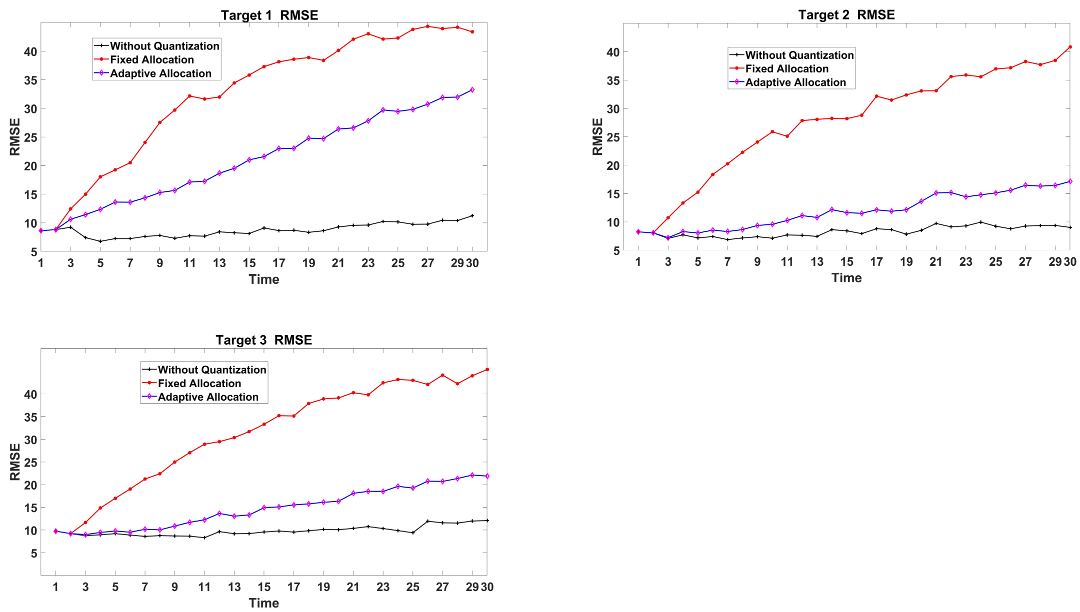


Figure 3.4: Comparison of RMSE for targets T1, T2, and T3 using fixed allocation and proposed adaptive allocation

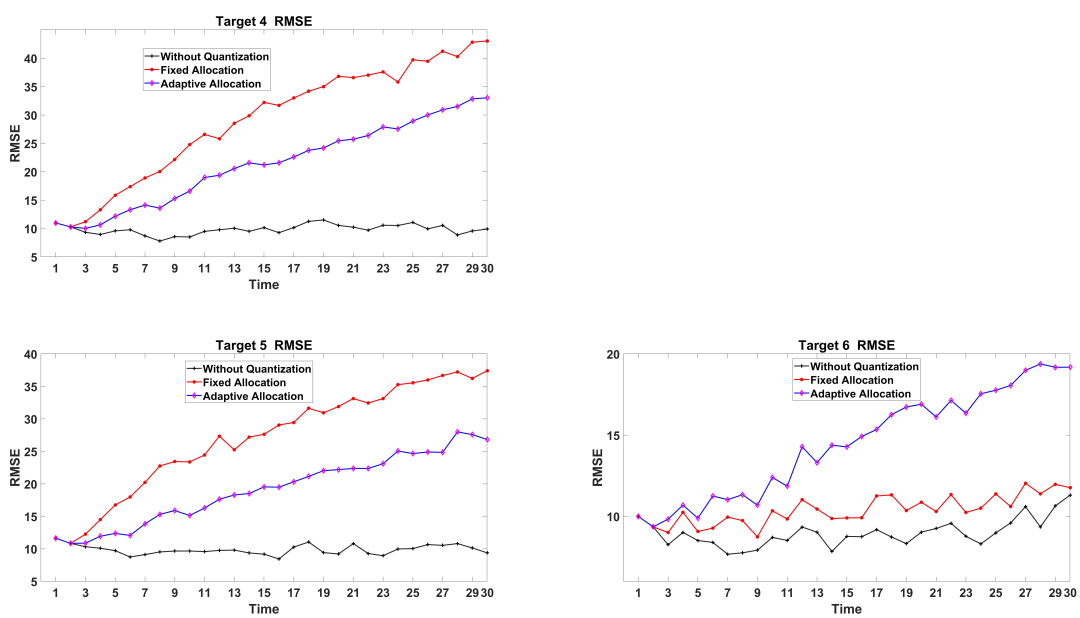


Figure 3.5: Comparison of RMSE for targets T4, T5, and T6 using fixed allocation and proposed adaptive allocation

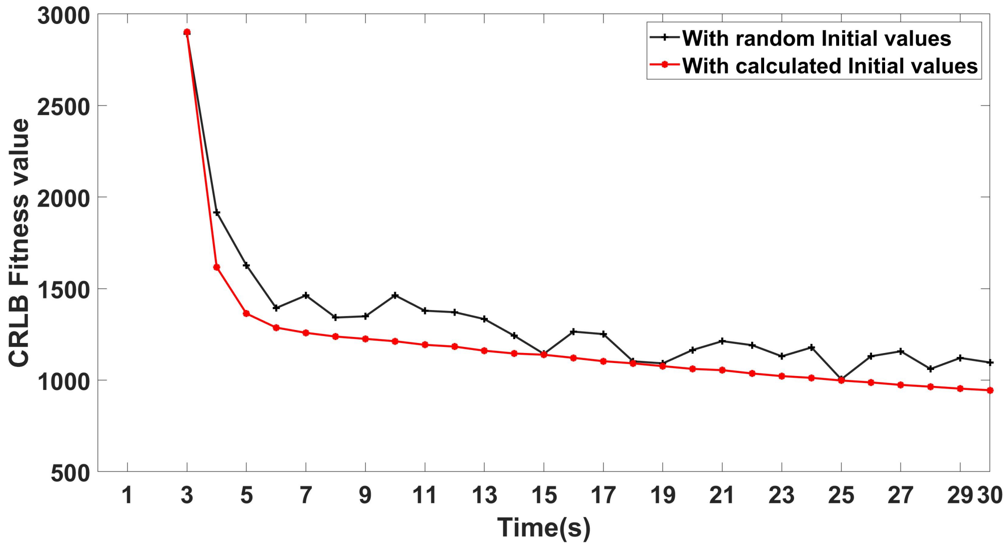


Figure 3.6: CRLB Fitness Value Comparison

as shown in Fig.3.7. In fixed allocation, each sensor is assigned to the closest FC. Using the adaptive method, each target at a given sensor node is assigned to an FC, which is chosen by solving the designed optimization problem. Each sensor has different error characteristics, like range error and azimuth error. The RMSE results are compared in the Fig.3.8, using fixed allocation and adaptive methods. In the third simulation, we demonstrate how the allocation of targets to FCs changes with a change in bandwidth availability for Simulation Scenario-II. In this scenario, for every 10 seconds, the bandwidth changes at FC1 and FC2. At time 1, the available bandwidths at FC1, FC2, and FC3 are 32, 6, and 6, respectively. At 10^{th} second, the available bandwidths are 17, 21, and 6 at FC1, FC2, and FC3, respectively. At the 20th second, the available bandwidths are 6, 36, and 6 at FC1, FC2, and FC3, respectively. Table.3.1, shows how the assignment of each target at each sensor node

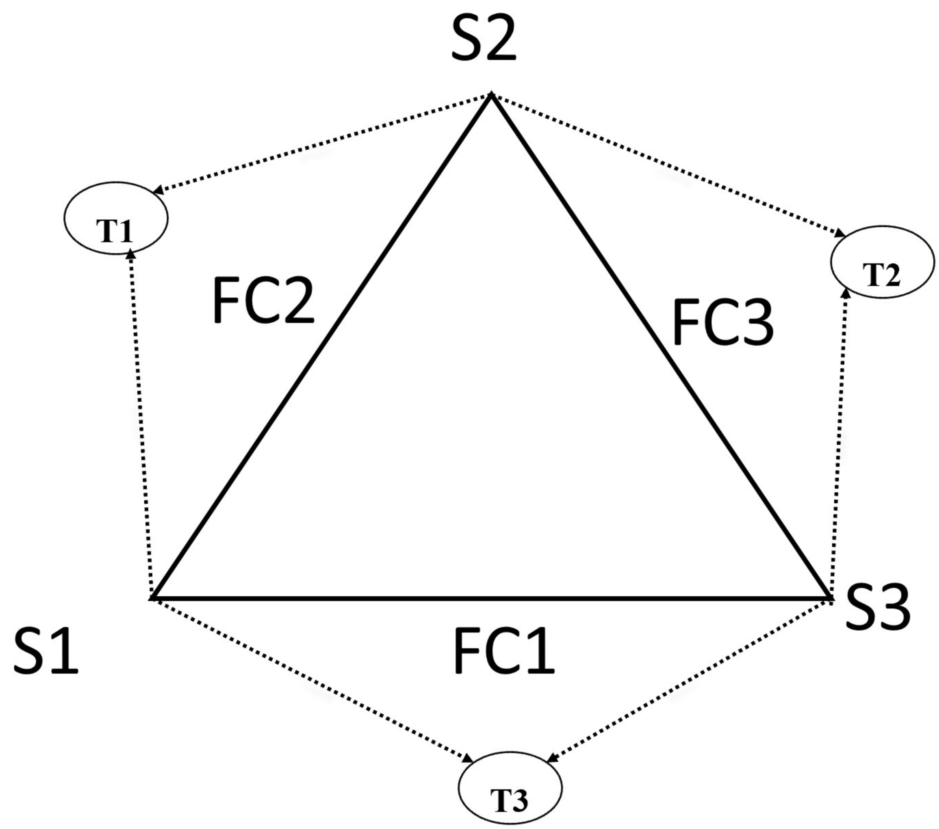


Figure 3.7: Simulation Scenario-II

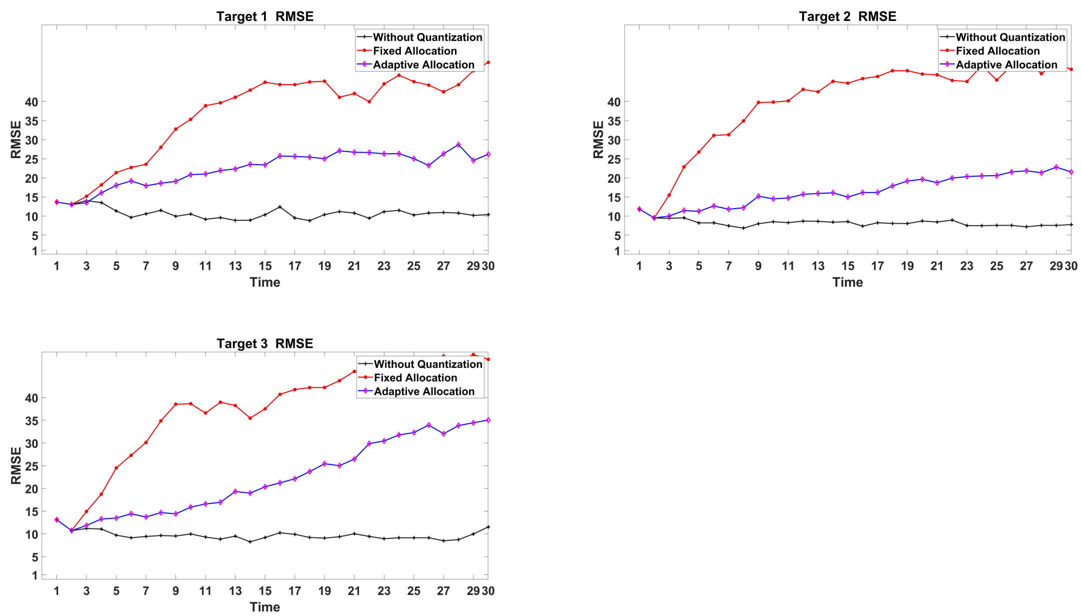


Figure 3.8: Comparison of RMSE for fused targets t1, t2, and t3 using fixed allocation and proposed adaptive allocation for Scenario-II

changes with the change in bandwidth. In the bracket at each FC, it shows how many bits are allocated to the particular target for a given sensor node. For example, at time interval 11, the target T1 at S1 was assigned to FC2 and allocated 7 bits for it. At the time instance, 4, T1 at S1 was assigned to FC1 with 7 bits, and the assignment was changed to FC2 at time interval 11. The assignment of T3 at S3 also changed from FC1 to FC2 from the time interval 4 to 11. The details of allocation are shown in Fig.3.9

Table 3.1: Targets to FCs Allocation

Time	T1-S1	T1-S2	T2-S3	T2-S2	T3-S1	T3-S3
4	FC1(7)	FC2(6)	FC1(7)	FC3(6)	FC1(8)	FC1(10)
11	FC2(7)	FC2(8)	FC1(9)	FC2(6)	FC1(8)	FC3(6)
21	FC2(10)	FC2(11)	FC1(6)	FC2(9)	FC2(9)	FC3(6)

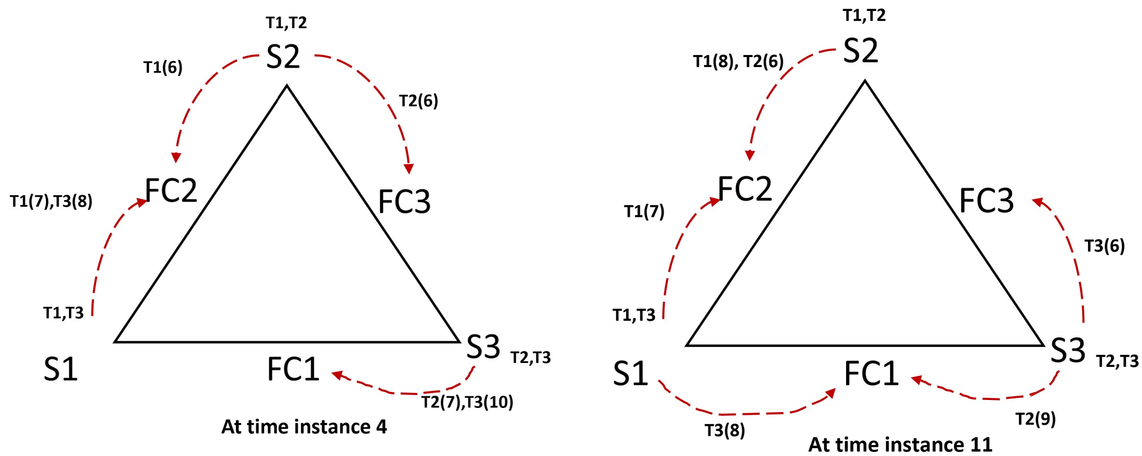


Figure 3.9: Targets to FCs Allocation For Scenario-II

In the fourth simulation, we show how the FCs are relocated and moved to a weighted centroid location according to the load assigned to each of the assigned sensors for the simulation scenario-I. The positions of S1, S2, and S3 are S1={10, 10, 0}, S2={1000, 1000, 0} and S3={2000, 100, 0}. The locations of FC1, FC2, and FC3 are FC1= {1000, 10, 1000}, FC2= {500, 500, 1000} and FC3= {1500, 500, 1000}. The new positions of FCs are calculated using Eq.3.3.25 and Eq.3.3.26. The new relocated positions are shown in Fig.3.10. At update time 29, the assignments are as follows. The targets t1, t2, t3, and t6 are assigned to FC1, and t4 and t5 are assigned to FC2 and FC3, respectively. The amount of data assigned to S1 is 24, and 8 bits are assigned to S3. The calculated locations of FC1, FC2, and FC3 are FC1= {507.5, 10, 1000}, FC2= {500, 500, 1000} and FC3= {500, 500, 1000}. The FC1 is moved closer to S1 as it is assigned more data to FC1. FC2 and FC3 are moved toward S2 as it communicates more data to FC2 and FC3. These newly calculated locations of FCs will be used at the next update time of 30.

In the fifth simulation, we demonstrated the assignment of targets to fusion centers

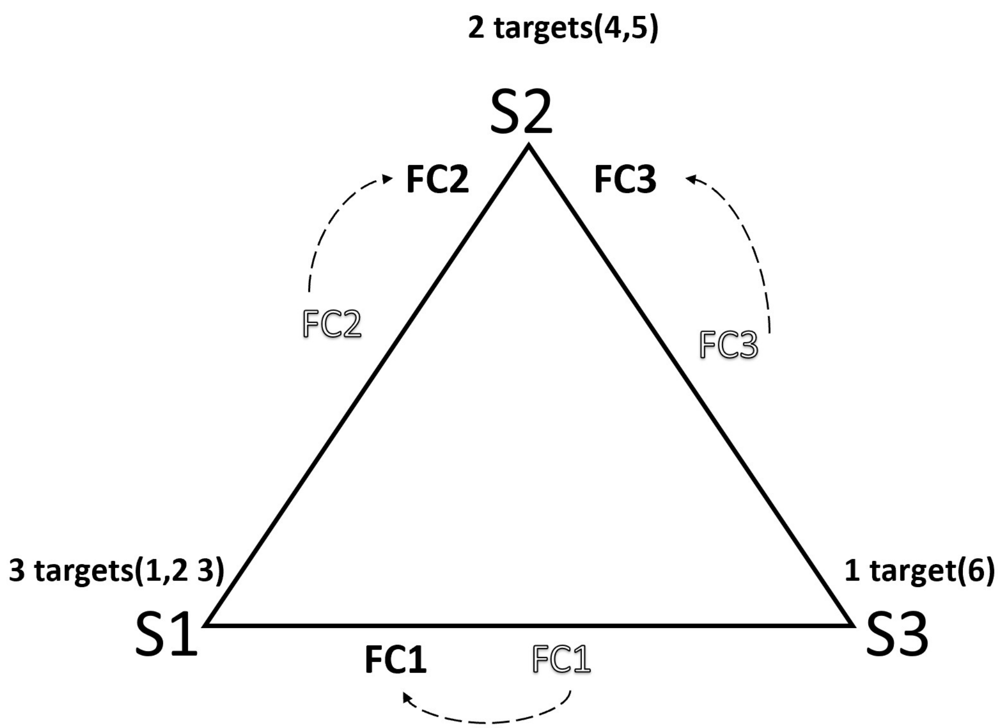


Figure 3.10: Relocation of Fusion Centers for Scenario-I

with 20 targets. In this scenario, we have 3 fusion centers, 10 sensors, and 20 targets, as shown in Fig.3.11. For the first case, the bandwidth availability at fusion centers

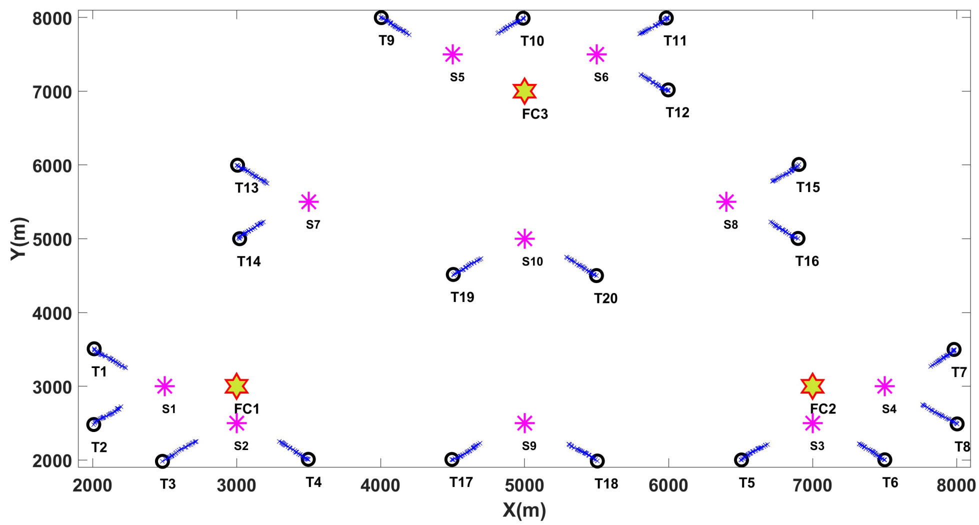


Figure 3.11: Simulation Scenario-III

FC1, FC2, and FC3 is {30, 30, 75}. Each target is tracked by only one sensor. That means one target is assigned to only one fusion center. The simulation is run for 100 Monte Carlo runs to get the assignment results. Five targets are assigned to FC1 and FC2 each. 10 targets are assigned to FC3. The assignment of targets to fusion centers and the bit allocation are shown in Table 3.2. The information given in the table is the target ID, and the fusion center it is assigned to, and the bits allocated to it.

Table 3.2: Targets to FCs Allocation

T1 - FC1(6)	T6 - FC2(6)	T11 - FC3(6)	T16 - FC3(9)
T2 - FC1(6)	T7 - FC2(6)	T12 - FC3(6)	T17 - FC2(6)
T3 - FC1(6)	T8 - FC2(6)	T13 - FC3(6)	T18 - FC1(6)
T4 - FC1(6)	T9 - FC3(9)	T14 - FC3(9)	T19 - FC3(9)
T5 - FC2(6)	T10 - FC3(6)	T15 - FC3(6)	T20 - FC3(9)

In the second case, we assume all the sensors are within the range of all three fusion centers' coverage. In this experiment, we want to demonstrate how the assignment changes if we do not optimize the distance. So we did not consider the optimization of the distance in this case. The bandwidth availability is {30, 30, 100} at FC1, FC2, and FC3 respectively. All the targets try to get more bandwidth if we do not have the distance objective and are assigned to the fusion center, where they can get more bandwidth. The bit allocation and the target assignment are shown in Table 3.3. On average, 14 targets are assigned to FC3, and 3 targets are assigned to FC1 and FC2 each.

Table 3.3: Targets to FCs Allocation

T1 - FC3(7)	T6 - FC2(6)	T11 - FC3(6)	T16 - FC3(8)
T2 - FC3(9)	T7 - FC1(7)	T12 - FC3(9)	T17 - FC3(7)
T3 - FC3(7)	T8 - FC3(6)	T13 - FC2(7)	T18 - FC3(6)
T4 - FC1(9)	T9 - FC3(6)	T14 - FC1(11)	T19 - FC2(8)
T5 - FC3(7)	T10 - FC3(8)	T15 - FC3(7)	T20 - FC3(7)

In our sixth simulation, we contrast the approximate algorithms with the Genetic Algorithm (GA)-based solution to the multi-objective integer optimization problem implemented in MATLAB. In Fig.3.12, we compare the RMSE of one target from the simulation scenario-I. Both approximate algorithms that produce suboptimal solutions and adaptive allocation using the GA algorithm operate quite similarly. When compared to the approximation greedy algorithm, the approximate algorithm-2 performs somewhat better but takes a little longer to execute. We have contrasted the execution times of three algorithms in Table 3.4.

Table 3.4: Time Comparison of Genetic Algorithm (GA) Algorithm and Proposed Approximate Algorithms in seconds

Targets	**GA**	**Approximate Greedy Algo-1**	**Approximate Algo-2**
6	0.6462	6.3304e-04	0.0011

3.7 Conclusion

In this paper, we have proposed a novel strategy for joint bandwidth allocation and assignment of targets to fusion centers for multi-target tracking in multiple distributed radar networks under cluttered background. The aim is to collect the best possible data from sensors for each target in resource-constrained situations to improve tracking performance and use the energy of sensor nodes and fusion centers optimally. We addressed the problem of associating targets to fusion centers and efficiently assigning the available bandwidth to the targets to improve the tracking performance and prolong the usage time of each of the fusion centers as well as sensor nodes by optimal

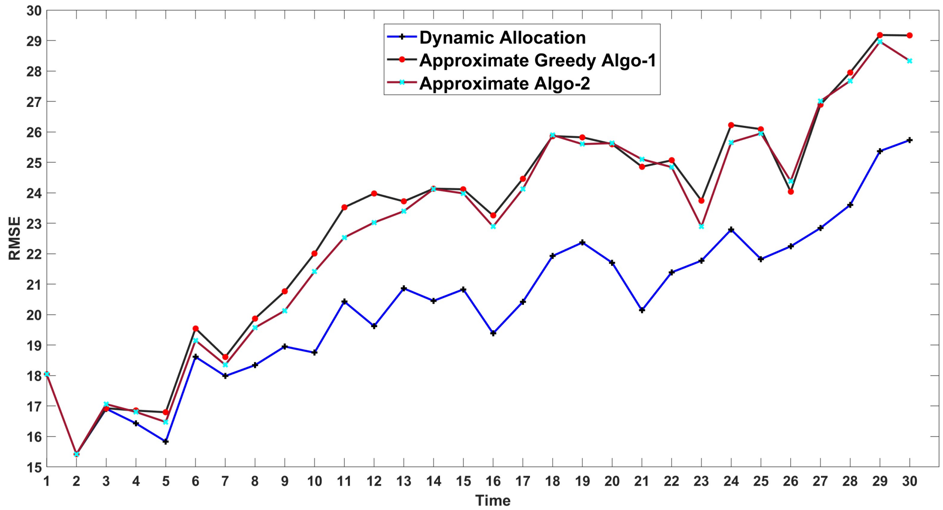


Figure 3.12: RMSE Comparison for GA and Approximate Algorithms for Target1 in Scenario-I

energy usage. We formulated the problem as a multi-objective integer optimization problem. The algorithm consists of three steps. In the first step, we associate the targets with fusion centers. The second step is the bandwidth allocation to targets at each of the sensors. In the third step, we relocate the fusion centers to the weighted centroid location to optimize the communication cost. We proposed an algorithm for creating initial values for the multi-objective integer optimization problem. Two approximate bandwidth distribution algorithms are proposed, which provide nearly ideal results at less computational time. We verified our analytical derivations with simulations. The simulation results demonstrate the efficiency and effectiveness of the proposed techniques.

Chapter 4

Efficient Performance Bounded Data Gathering for Distributed Multi-Target Tracking

4.1 Introduction

Wireless sensor networks are proving useful in a variety of settings. These wireless sensors are of low-cost, low-power, and small-size. They are spatially distributed for monitoring and recording ambient environmental conditions and are widely deployed in diverse applications ranging from military scenarios to civil scenarios, such as intrusion detection, homeland security surveillance, volcano supervision, soil monitoring for smart agriculture, and forest fire inspection. WSN nodes often employ an independent power supply to facilitate deployment in numerous challenging situations. However, this also means that WSN nodes have very scarce energy, memory, and other computing resources. The environment where these sensor nodes are deployed can be harsh, dangerous, and sometimes hostile. In these kinds of situations, it is generally hard to replace or change energy sources. Replenishment of these critical resources, like energy supply, is possible, but it can be very expansive due to the environment they are in. Sonobuoys are examples of wireless sensors that are deployed for underwater surveillance, usually for anti-submarine warfare or any other military operation. Data is collected from all these sensors to get a global picture of the tracking region. Data collection can be done by using either an aerial vehicle like a drone or a ship[18]. To ensure improved data collection and effective use of scarce resources, these data collectors should be relocated along the data load as the targets travel from the tracking region of one sensor to another. A data collector can be a slow moving or fast moving vehicle. For fast moving targets, the data collectors should also be able to move along at the same pace. The amount of data that needs to be communicated from the sensor node to the data collector determines the energy consumption at both locations. A sensor node uses energy for communication, processing, and sensing, which together make up its three main energy sources. According to experimental observations, calculation energy is often insignificant in comparison to communication energy in many applications. Since the efficiency of the data collection is significantly impacted by the restricted on-board energy supply. Data collection that uses less energy is therefore crucial. It is crucial to reduce the energy consumption of installed sensor nodes and data collectors for network longevity, notably in situations when sensor nodes are required to keep an eye out for odd events like earthquakes, floods, and other natural calamities. The communication's energy consumption can be reduced by picking the relevant data for just interested targets. So choosing the relevant data collector is an important decision to make for efficient data collection. The work that has been presented here can be used and put into practice for a look-ahead scenario in which we forecast the state of affairs for the upcoming few time intervals to ascertain whether we need more data collectors because of an increase in load or fewer data collectors because of a decrease in load, in the designated tracking area. For instance, instead of predicting the state for the next time interval, we predict the state for the next 10 time intervals, which provides extra time to deploy more data collectors or remove extra data collectors. Since mobility requires a lot of energy and time, it is preferable to limit the movement of these data collectors as much as possible. So we divide the tracking region into clusters and deploy the data collectors. A lot of work is done to place the data collectors according to the coverage radius using various algorithms. We assume the data collector stays in the same location to collect the data at a specific point in time, and for subsequent data collection iterations, the data collector may be in a different location. The maximum speed and update interval, however, affect how far it can travel. There are times when cost or availability prevent the deployment of enough data collectors for every region. In such cases, a certain number of data collectors must be made available to cover every region in order to collect data. We must choose which data collector will cover each region when it comes to coverage path design, which is the crux of the issue. In many applications, not all the targets' information is important to the end-user. Many times, if there are more targets in the tracking region, there will be certain significant targets for which we have higher expectations for tracking accuracy. So we can prioritize the targets using the accuracy requirement to make efficient use of the resources. In this paper, we considered two important resources, energy availability at the sensor node and at the data collector, in terms of the amount of data they can communicate.

The rest of the paper is organized as follows. In Section 4.2, we present the related work and the contributions. Section 4.3 provides the system model and problem formulation. Details of the initial placement algorithm are described in Section 4.4. Next, we describe the association of sensors to data collectors in the overloaded region in Section 4.5. In Section 4.6, we deal with the coverage path planning issue when there are a fixed number of data collectors available to cover all the regions. In Section 4.7, we provide the simulation results, and finally Section 4.8 concludes the paper and discusses some future research directions.

4.2 Related Work and Contributions

An efficient deployment approach was proposed in [49] based on the circle packing theory that leads to a maximum coverage while each UAV uses a minimum transmit power given a desired geographical area that needs to be covered by multiple UAVs. A three-layer framework is proposed in [89] for mobile data collection in wireless sensor networks, which includes the sensor layer, cluster head layer, and mobile collector layer. The framework employs distributed load balanced clustering and dual data uploading. A two-step solution was proposed in [24] for the multi-UAV data collection problem in clustered IoT networks, where sensed data have time deadlines. In the first step, the number and locations of cluster heads, which gather data from associated IoT sensors, are optimized using a customized K-means approach. Subsequently, an energy-efficient data collection framework that uses the minimal number of UAVs is presented. In [43], a market based dynamic bit allocation scheme was studied for target tracking in energy-constrained wireless sensor networks using quantized data where the fusion center acts as a customer, and sensors act as producers and the prices of purchasing bits from sensors and the price of unit, energy balances the market. In [70], the UAV location and user association problem from a load-balancing perspective was investigated. First, a clustering method was introduced to initially place UAVs using the area of maximal local density. strategy, which tried to minimize the maximum traffic demand among UAVs, so that the traffic capacity among UAVs can be balanced as much as possible, was studied. Third, a UAV location algorithm with the method of the backtracking line search algorithm to refine the load balance among the systems was proposed. Finally, after determining the horizontal locations of UAVs, the altitude of each UAV is adjusted to save power consumption. Instead of sending the entire sensor data to the fusion center, a subset of sensors is activated using sensor management policies to satisfy the application requirements using the minimal resources that are available. In the sensor selection problem, a subset of sensors is selected at every update time while tracking a target that gives optimal performance while using minimal resources. Using sensor collaboration, dynamically select a subset of sensors over time to optimize tracking performance in terms of mean square error. As an example, in the sensor selection problems, a decision is made on whether a sensor transmits its measurement or not based on the constraint of the total number of selected sensors[90]. Power allocation and selecting the number of sensor nodes to optimize the critical resources of the system are addressed in many papers[79, 83, 27]. The goal of the dynamic case deployment in [34] is to minimize time-averaged UAVs power consumption within predefined limitations, whereas the goal of the static case deployment is to discover an ideal number of static UAVs deployment to minimize ground terminal transmission power. Through a Lagrangian approach, the authors investigated the appropriate placement and movement of several UAVs to provide the best time-averaged performance. By choosing an ideal stop location near deployed sensors to collect data and then taking an ideal path to finish the data collection trip, the authors of [25] proposed an energy-efficient trajectory optimization proposal. The difficulties of UAV deployment and relocation have been approached from several angles. For static deployment, [6] consider where UAVs should be placed to maximize coverage and offer several algorithms. These studies presuppose that a UAV can cover a ground terminal as long as their separation is no greater than a specific amount. The goal of the work in [40] is to ensure that each distributed ground terminal (GT) is within the communication range of at least one MBS, thereby reducing the number of MBSs required to provide wireless coverage for a group of GTs. In [32], the authors use space-division multiple access to improve the trajectory of a single UAV serving numerous mobile GTs. Future GT locations are forecasted by a Kalman filter, which then determines the UAV trajectory. In [53], the authors presented a unique system for quickly deploying and relocating UAVs to gather data from ground IoT devices during the uplink. To minimize the total transmit power of the IoT devices within their SINR limitations, we have specifically identified the jointly optimal UAV positions, device association, and uplink power control. In [33], a heterogeneous two-tier network that transmits data to heterogeneous fusion centres from large-scale wireless sensors via heterogeneous access points was discussed. The overall network power consumption is used as the cost function for the optimization problem of the deployment of heterogeneous nodes.

The load variation at the sensor nodes and how it impacts the necessary number of data collectors are not taken into account by the currently available studies.

Given that transmitters contact the medium using separate spectrum bandwidths, [22] provides three approximations for the power or/and bandwidth distribution. [36] investigates the problem of UAV-enabled data collection for high information freshness in wireless sensor networks, where one UAV is sent out to gather data from ground Sensor Nodes (SNs). The Age of Information (AoI) of each SN, which is calculated as the time the UAV spent in flight after leaving the SN plus the time it took to upload its data, serves as a gauge of how recent the information is. The authors of [75] examine multi-UAV collaborative data collection systems, in which numerous UAVs fly or hover while collecting data from two-dimensional dispersed devices. The goal is to reduce the total flight time of UAVs while enabling each device to effectively upload data while using a minimum amount of energy. The effectiveness of cooperative UAV clustering on terrestrial cellular networks with caching EH-powered UAVs was investigated in [76]. The successful transmission probability for a random GMT was computed using Gamma approximations for the aggregated signal strength, and a user-centric cooperative UAV clustering technique was suggested. The study in [13] looked at how autonomous UAVs plan their flight paths in order to establish a flight path that would be effective enough to visit all the regions of interest. First, a precise formulation was suggested based on mixed integer linear programming to find the best flight paths for UAVs. After that, a clustering-based approach was introduced with the aim of reducing the time required for UAVs to complete tasks by grouping regions into clusters and determining workable flight paths. For the purpose of addressing the computational difficulties brought on by the heterogeneity of UAVs, the authors in [14] presented a novel capability rank to evaluate the performance of UAVs used in the search tasks. Then, in a way inspired by density-based clustering analysis, divide regions into groups based on their densities, which are computed via relative distances and scan areas. A search-based method based on symbiotic organisms is then successfully used to modify the visiting order of each region aggregated into the same groups. As far as we are aware, no prior attempts have included calculating bandwidth based on the targets' stated accuracy and deploying a minimal number of data collectors to cover all sensors with the specified load. The significant contributions of this paper are listed below.

- We calculate the minimum number of data collectors with limited bandwidth and coverage area required to cover all the sensors and get the given accuracy results for each target.
- We propose an iterative approach to placing the data collectors such that as the targets move from one sensor region to another, the data collectors are relocated to get better performance and optimal usage of the data collectors.
- We formulate an algorithm for the initial placement of data collectors using information on the number of targets at each sensor node and their accuracy requirements. We model the problem using the modified bin packing problem. As load changes, we also cover the procedure for adding and removing new data collectors.
- We model the association of data collectors to the sensor nodes using a Multi-Objective Optimization problem, where a single sensor is assigned to only a single data collector.
- We use the lexicographic approach to solve the Multi-Objective Optimization

problem, which effectively generates the optimal solution by defining the sequential optimization stages.

- We propose an approximate algorithm for the initial placement of data collectors and their association with sensors.

- For the purpose of covering the regions with a specific number of fixed data collectors, we define a coverage path planning problem.

- To address the coverage path planning issue, we propose the approximation approach known as Minimum Total Time (MTT).

4.3 System Model and problem formulation

In this section, the description of the problem and a formulation based on the BCRLB, which gives a measure of the tracking accuracy, are presented. Consider a total of N

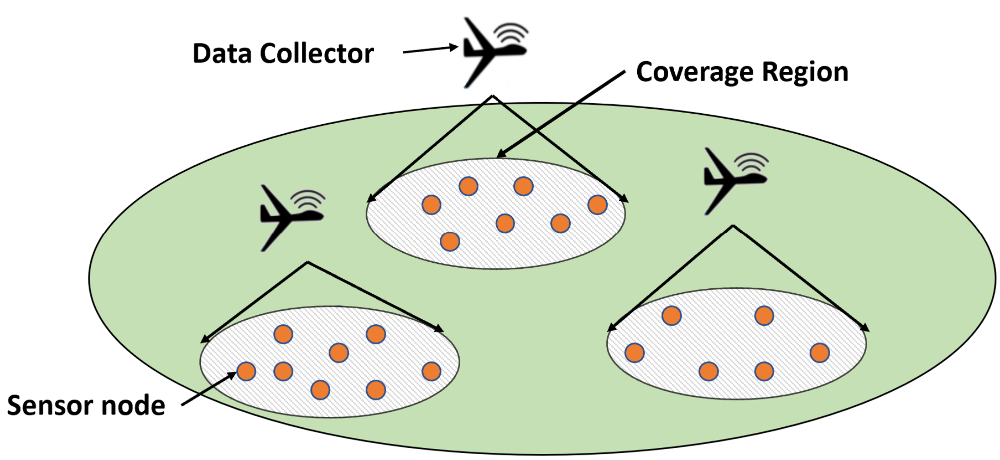


Figure 4.1: Sample Scenario Representation

sensors deployed in the ROI, and their positions are $\{s_n = [x_n, y_n]', n = 1, 2, ..., N\}$.

They can simultaneously track M targets labelled as 1,2,..., M, in the surveillance region. The observation interval between two contiguous tracking frames is denoted by T. Then, at the discrete time k (equivalent to continuous time kT). X_k^t is the target state of target t at time k is defined as $X_k^t = [x_k^t, y_k^t, \dot{x}_k^t, \dot{y}_k^t]^\top$, in which $[.]^\top$ is the transpose operation, x_k^t and y_k^t are the target positions, and $\dot{x}_k^t$ and $\dot{y}_k^t$ denote the velocities in horizontal and vertical directions. v_k is white Gaussian process noise with zero mean and covariance matrix Q. How many data collectors with limited bandwidth capabilities must be placed in order to achieve the specified accuracy for each target? is a crucial topic that we address in this work. Let η_k^i be the desired accuracy of the target i at the time instance k. The sample scenario with three data collectors and the sensor nodes inside their coverage area is shown in Fig.4.1. The placement of data collectors based solely on coverage area is insufficient in many applications to obtain the required performance in terms of tracking precision. If, for instance, every sensor node is within the range of a single data collector, then just one data collector needs to be set up. A single data collector may not be sufficient to achieve the required performance, though. If we want to achieve the specified precision, we might need to deploy more data collectors. The accuracy criterion is subject to alteration over time, and the performance requirements for various targets may vary. The Bayesian CRLB determines the lower bound of the error covariance of target state estimation. The accuracy requirement of a given target indirectly reflects the importance of the target. Thus, the predicted BCRLB is usually used as the optimization criterion for radar resource allocation. The BCRLB shows that the mean squared error (MSE) of any estimator can not go below a bound, which is given by [83, 48, 90]

$$\mathrm{E}\left\{\left[\mathbf{x}_k^i - \hat{\mathbf{x}}_k^i\left(B_k^i\right)\right]\left[\mathbf{x}_k^i - \hat{\mathbf{x}}_k^i\left(B_k^i\right)\right]^\top\right\} \geq \left[\mathbf{J}_{\mathbf{x}_k^i}\left(B_k^i\right)\right]^{-1} \tag{4.3.1}$$

where E is the error matrix of the estimator and $\mathbf{J}$ is a Bayesian information matrix. The Bayesian information matrix (BIM), i.e., the inverse of the BCRLB matrix, can be denoted by the sum of two terms. $\mathbf{J}_P$ denotes the prior information, and $\mathbf{J}_Z$ denotes the information from the measurements or data. BIM can be written as

$$\mathbf{J}_{\mathbf{x}_k^i}\left(B_k^i\right) \triangleq \mathbf{J}_{P,k} + \mathbf{J}_Z\left(B_k^i, \mathbf{x}_k^i\right) \tag{4.3.2}$$

where $\mathbf{J}_{P,k}$ corresponds to the prior information regarding the target state:

$$\mathbf{J}_{P,k} = \left[\mathbf{Q}_T + \mathbf{F}\mathbf{J}_{\mathbf{x}_{k-1}^i}^{-1}\left(B_{k-1}^i\right)\mathbf{F}^\top\right]^{-1} \tag{4.3.3}$$

and the information from measurements is given as:

$$\mathbf{J}_Z\left(B_k^i, \mathbf{x}_k^i\right) = \mathrm{E}\left\{\nabla_{\mathbf{x}_k^i}^\top \mathbf{h}\left(\mathbf{x}_k^i\right)\left[\mathbf{R}_k^i\left(B_k^i\right)\right]^{-1}\nabla_{\mathbf{x}_k^i}\mathbf{h}\left(\mathbf{x}_k^i\right)\right\} \tag{4.3.4}$$

Eq.4.3.4 is simplified and replaced by the predicted value. So the total information is given by:

$$\mathbf{J}_{\hat{\mathbf{x}}_{k|k-1}^i}\left(B_k^i\right) = \mathbf{J}_{P,k} + (\mathbf{H}_k^i)^\top[\mathbf{R}_k^i(B_k^i)]^{-1}\mathbf{H}_k^i \tag{4.3.5}$$

In this paper, the DET of the BCRLB matrix is used as the metric to measure the tracking performance.

$$\mathcal{C}_{\hat{\mathbf{x}}^i_{k|k-1}}\left(B^i_k\right) = \det\left\{\mathbf{J}^{-1}_{\hat{\mathbf{x}}^i_{k|k-1}}\left(B^i_k\right)\right\} \tag{4.3.6}$$

Further, the following assumptions are made to simplify the problem.

Assumption 1: We know the number of sensors and their locations.

Assumption 2: There are a known number of targets at each sensor.

Assumption 3: We are able to relocate the data collector whenever required based on its maximum speed and update time.

Assumption 4: We know the maximum coverage region of each data collector and bandwidth limitations.

Assumption 5: For each of the confirmed targets, we are given the desired accuracy requirement.

Assumption 6: Each sensor node is associated with only one data collector.

4.3.1 Minimum number of Data Collectors with Fixed coverage Radius

As the first part of the problem, we want to determine the minimum number of data collectors with a fixed coverage radius, CR required to cover all the given sensors. The grouping of sensors is called 'clustering'. In this section, we form clusters of sensors based on the coverage radius. We adopt a recursive approach to determine the minimum number of data collectors based on the coverage radius. Let $f(N, CR)$ be the required number of data collectors needed to cover N sensors with a coverage region with Radius CR. Define p_i to be the average point of i points taken all at once, where $1 \leq i \leq N$. So the coordinates of p_i, will be

$$\left(\frac{1}{i}\sum_{k=1}^{i} x_k, \frac{1}{i}\sum_{k=1}^{i} y_k\right) \tag{4.3.7}$$

where x_k, y_k are the coordinates of the k^{th} given sensor. Calculate p_i for every i ranging from 1 to N. Note that there may be multiple possibilities for p_i depending on which i sensors we choose, particularly, $\binom{N}{i}$ possibilities. Now, construct a circle of radius CR centered at p_i in each case, and note the number of sensors it encloses. The case where the maximum sensors, say, H are enclosed is what we are interested in, if there is more than one case, include that in the further calculations too. Then we have,

$$f(N, CR) = 1 + f(N - H, CR) \tag{4.3.8}$$

And then we can work with this recursion to get the answer. It means at the start of the recursion we can form a group of a maximum of H sensors out of N sensors and deploy one data collector to cover H sensors. Then we continue to find the number of minimum data collectors required for the rest of $(N - H)$ sensors with coverage range CR. If we have different coverage range data collectors, we need to arrange the data collectors in some order, either based on the coverage range or bandwidth capability. Then form clusters with the set of ordered data collectors. For example, $CR1, CR2, CR3,$ and $CR4$ are coverage ranges for the data collectors $DC1, DC2, DC3,$ and $DC4$. Then we first form the cluster for DC1, then DC2, and so on until all the sensor nodes are covered. This step is optional if the given ROI is small, and we can treat the whole ROI as one cluster. If the entire ROI is one cluster, it gives better performance in terms of the usage of the data collectors. If an ROI is very large, dividing it into small clusters is beneficial in terms of computational time. So, the formation of clusters of sensors using the coverage radius of data collectors is optional. The rest of the problem formulation works even without forming clusters based on radius. In the next subsection, we describe how we can calculate the bits required to get a given accuracy for a target.

4.3.2 Minimize Total Bit Allocation to Get a Given Accuracy

The question we ask in this section is: for each cluster of sensors, how many data collectors are required to get the given accuracy performance? For some clusters, one data collector may be sufficient if the targets are fewer. For other clusters, one data collector may not be enough to meet the MSE requirement. In this section, we compute the total bandwidth or bit requirement from each target to meet the desired performance. Due to bandwidth limitations, each sensor can communicate one measurement for a target, and it quantizes the measurement before sending it to the data collector. Quantization helps reduce the amount of data to communicate. However, it introduces quantization errors due to the loss of information. As we are given the MSE requirement for each target, how much to quantize depends on the given accuracy. For instance, if we need good accuracy, then we have to send more data. So there is a trade-off between the amount of data to send, and its accuracy. We formulate the problem of calculating the number of bits required to get the given accuracy as an optimization problem. The optimization problem in Eq.4.3.9 is a non-convex optimization problem with the given constraints from Eq.4.3.10 to Eq.4.3.11. In general, solving constrained, nonlinear, non-convex optimization problems is a very challenging task and commonly requires extensive computational load. We use the Genetic Algorithm(GA) to solve Eq.4.3.9.

$$\arg\min_{\mathbf{B}_k} \quad \mathbf{1}^\top \mathbf{B}_k \tag{4.3.9}$$

$$\text{s.t.} \quad \mathcal{C}_{\hat{\mathbf{x}}^t_{k|k-1}}\left(B^t_k\right) \leq \eta^t_k, \quad t = 1, 2, \ldots, M \tag{4.3.10}$$

$$B_{\min} \leq B^t_k \leq B_{\max} \tag{4.3.11}$$

By solving the above optimization problem, we can get the bandwidth requirement for the given cluster of sensors. Based on the computed bandwidth values, we can compute the number of data collectors with given bandwidth availability to be deployed using the following initial placement algorithm.

4.4 Initial Placement of data collectors

Even though one data collector can cover all the sensor nodes, due to the greater number of targets and desired accuracy requirements in the region, we may need to deploy more data collectors in order to meet the MSE demand. The question we ask in this section is, if we know the bandwidth requirements at each sensor node, then how many data collectors are to be deployed, and where should we place them initially? In this section, we describe how to initially place the data collectors if you know the number of targets at each sensor node and their accuracies. The maximum number of data collectors and their bandwidth capacities have been provided. Let $B = [B_1, B_2, ..., B_n]$ be the set of data collectors to be deployed with the given bandwidth availability. The sensor node weights are $W = [w_1, w_2, ..., w_s]$, representing the bandwidth requirement at each sensor node, which equals the sum of all targets bit requirement. The problem is similar to the bin packing problem, which is an NP-hard problem. The bins in this case are the data collectors, with a weight of B_j for each data collector j. The objects to place in the bins are the sensor nodes, with weight equal to the bandwidth requirement at each sensor node. The weight of each sensor node is w_i at sensor i. Assign each sensor node to one data collector so that the total weight of the items in each bin does not exceed B_j, and the number of bins used and the distance between the data collector and the sensor nodes should be kept to a minimum. The mathematical formulation of the problem is as follows.

$$\min \sum_{j=1}^{n} y_j \tag{4.4.1}$$

$$\min \sum_{j=1}^{n} \sum_{i=1}^{s} x_{ij} * y_j * d_{ij} \tag{4.4.2}$$

Subject to

$$\begin{cases} \text{C1: } \sum_{i=1}^{s} w_i x_{ij} \leq B_j y_j \quad \forall j \in n \\ \text{C2: } x_{ij} * y_j * d_{ij} \leq CR_j \\ \text{C3: } \sum_{j=1}^{n} x_{ij} = 1 \quad \forall i \in s \end{cases} \tag{4.4.3}$$

$$x_{ij} = \begin{cases} 1, & \text{if sensor } i \text{ is assigned to DC } j \\ 0, & \text{otherwise} \end{cases}$$
$$y_j = \begin{cases} 1, & \text{if data collector } j \text{ is used} \\ 0, & \text{otherwise} \end{cases} \tag{4.4.4}$$

The first objective in Eq.4.4.1 is to minimize the number of data collectors to deploy. The second objective in Eq.4.4.2 is to minimize the sum of the weighted Euclidean distances between the data collector and the assigned sensor nodes. The amount of bandwidth allotted to a single data collector is shown C1 in Eq.4.4.3, and it shouldn't be greater than the bandwidth that is really available. C2 in Eq.4.4.3 ensures the distance between the sensor node and the data collector is not greater than the coverage radius of the data collector. According to C3 in Eq.4.4.3, only one data collector is assigned to each sensor node. We can assume that the weight of each sensor is not more than any bin's capacity.

$$w_i \leq B_j, \quad \forall i \in s \quad \forall j \in n \tag{4.4.5}$$

We can know the minimum number of data collectors (DC_{min}) required, which is calculated as

$$DC_{min} >= Ceil[\text{Total bandwidth / max(Bin Capacity)}] \tag{4.4.6}$$

We will get the list of data collectors and their associated sensors once we solve the bin packing problem. And the data collectors are initially placed at the weighted centroid location, which is given in Eq.4.4.7 and Eq.4.4.8. The weighted centroid is calculated using the bandwidth requirement at each sensor node as a weight. Let S_j be the set of sensors associated to the data collector, j. For instance, if the set S_j, has m the number of sensors, then the weighted centroid (x_c, y_c) is calculated as follows.

$$x_c = \frac{\sum_{k=1}^{m} w_k * x_k}{\sum_{k=1}^{m} w_k} \tag{4.4.7}$$

$$y_c = \frac{\sum_{k=1}^{m} w_k * y_k}{\sum_{k=1}^{m} w_k} \tag{4.4.8}$$

We propose an approximate algorithm, Algorithm 5, for calculating the number of data collectors, which is similar to the bin packing problem, which is NP-hard and finding an exact minimum number of bins takes exponential time. The approximation algorithms are not guaranteed to find the optimal solution, but their running time is short. In Algorithm 5, we try to minimize the distance between the data collector and the sensor nodes by selecting the closest sensor node while calculating the minimum number of data collectors. The main idea of this algorithm is to first choose the next sensor with maximum bandwidth requirement and associate it to the next available data collector. We keep including the sensors that are nearest to the computed centroid location so far until the data collector bandwidth limit is reached, or no other sensor can fit in the group. In Algorithm 5, B_j at the step.6 is the bandwidth availability at the data collector j. A sensor node is not *VISITED* if it is not yet associated with any data collector. w_i is the bandwidth requirement at the sensor node, i which depends on the number of targets and their accuracy requirements. A sensor node is *CHECKED* if we have already checked if it can be associated with the given data collector. If a node is marked as checked but not visited, it means the bandwidth of the sensor node is greater than the available bandwidth of the given data collector. In step. 15, i is assigned to the next nearest sensor node to the current centroid location, which is not visited.

Algorithm 5 An Approximate Algorithm to compute the number of Data Collectors and their Initial Placement

Require: Given sensors, and bandwidth requirements at each sensor node.

Ensure: Compute the minimum number of data collectors required and the initial placement of data collectors.

1: Mark all the sensor nodes as not VISITED. not all sensors are visited

2: Choose the next available data collector j. S_j is set to null, which is the set of sensors to be associated with the data collector j.

3: Choose a not visited sensor node s_i, with maximum weight.

4: Mark all not visited nodes as not checked. $B_j > 0$ and not all sensors are checked $w_i \leq B_j$

5: $B_j \leftarrow B_j - w_i$.

6: Insert s_i in S_j.

7: Mark s_i as visited and checked.

8: Compute the weighted centroid location.

9: Mark the sensor s_i as checked.

10: $i \leftarrow$ the next nearest not visited sensor node

11: The data collector j is placed at the weighted centroid of all the sensors in the set S_j.

12: Sensors without targets are assigned to the nearest DC to make sure all the sensors are covered by at least one data collector.

In the following section, we discuss how to associate sensors to data collectors once they are deployed.

4.5 Association of the sensor nodes to the data collector in overloaded Region

First, we place the data collectors according to the initial placement algorithm. The association of sensors with the data collector depends on the location of the data collector. So, the problem of finding the best locations for data collectors and associating sensors with data collectors is interconnected. The main idea here is to move the data collectors adaptively as the targets move. As the targets move from one sensor region to another with time, the number of targets at each sensor changes. We iteratively optimize the location of data collectors and their associations. So, the data collectors are adaptively placed according to the load at each sensor node which is computed using the number of targets and their accuracies for efficient use of data collectors as well as better coverage of targets. Suppose one sensor can be associated with only one data collector, then we need to find the association between sensors and data collectors. We have discussed in our other work how to assign sensor nodes to multiple data collectors so that different targets at each sensor node can be assigned to different data collectors. Eq.4.5.1 is the first objective to minimize the bandwidth allocation to the targets. Once a sensor is assigned to a data collector, all the targets that belong to the sensor are assigned to the corresponding data collector. W_1 is the weight given to the objective.

$$\min \left\{ \sum_{i=1}^{N} \sum_{j=1}^{K} W_1 * A_{ij} * \sum_{t=1}^{M} B_{ij}^{t} \right\} \quad (23) \tag{4.5.1}$$

The second objective in Eq.4.5.3 is to minimize the distance between the sensor node and the data collector. The communication energy depends on the distance between the source and the destination. Then, in order to transmit m bits successfully to the data collector, each sensor should transmit its measurement with energy.

$$e_i(m) \propto d_{ij}^2 \tag{4.5.2}$$

W_2 is the weight assigned to this objective.

$$\min \left\{ \sum_{i=1}^{N} \sum_{j=1}^{K} W_2 * A_{ij} * d_{ij} \right\} \tag{4.5.3}$$

- i is the index of sensor devices, and N is the total number of sensors.
- j is the index of DCs, and K is the total number of DCs.
- t is the index of targets, and M is the total number of targets.

The first constraint is to make sure all the targets achieve their accuracy requirements.

$$\mathcal{C}_{\hat{\mathbf{x}}^t_{k|k-1}} \left(B^t_k \right) \leq \eta^t_k, \quad \forall t \in \mathcal{M} \tag{4.5.4}$$

The second constraint is to make sure one sensor is assigned to no more than one data collector.

$$\sum_{j=1}^{K} A_{ij} \leq 1 \quad \forall i \in \mathcal{N} \tag{4.5.5}$$

The third constraint is to make sure the total allocated bandwidth to the sensor nodes does not exceed the data collector's bandwidth.

$$\sum_{i=1}^{N} A_{ij} * \sum_{t=1}^{M} B^t_{ij} \leq B_j \quad \forall j \in \mathcal{K} \tag{4.5.6}$$

The fourth constraint is that the distance between the sensor node and the data collector should not exceed the maximum coverage radius of the data collector. Let d_{ij} be the distance between the sensor node i and the data collector j. CR_j is the coverage radius of the data collector j.

$$W_3 * A_{ij} * d_{ij} \leq CR_j \quad \forall i \in \mathcal{N} \quad \forall j \in \mathcal{K} \tag{4.5.7}$$

The fifth constraint is that each sensor node should be covered by at least one DC, even if there are no targets at the sensor node.

$$\sum_{j=1}^{K} A_{ij} \geq 1 \quad \forall i \in \mathcal{N} \tag{4.5.8}$$

We can combine the second and fifth constraints into a single constraint.

$$\sum_{j=1}^{K} A_{ij} = 1 \quad \forall i \in \mathcal{N} \tag{4.5.9}$$

The last important constraint is given in Eq.4.3.10 and Eq.4.3.11. It means each target should achieve its given accuracy results, and each target should be assigned the bandwidth which lies between B_{min} and B_{max}.

4.5.1 An Approach to Solve Multi-Objective Optimization Problem

There are many ways to solve the Multi-Objective Optimization(MOO) problem. It's not a trivial task to solve the MOO problem. Given a sequence of cost functions, an optimization criterion is said to be lexicographic whenever there is a preference in the order in which the cost functions are optimized[59]. The sequential optimization of the lexicographic approach for solving multi-criteria problems is implemented by finding the generalized solutions of a system of inequalities defining the sequential optimization stages. The algorithm effectively generates an optimal solution at every sequential optimization stage. Not only does it establish a priority in your preferences, but also each optimization criterion, is defined in such a way that the set of potential solutions is subsequently reduced. The highest priority objective is to find a feasible basis, then it is refined, improving its optimality step by step. However, it can be simplified by making it a sequential optimization problem where the optimization criterion is lexicographic. A lexicographic objective function f is a combination of multiple objective functions f_1, f_2, and f_3, where an objective function f_1 is more important than f_2 which in turn is more important than f_3. The MOO problem in Section E can be solved sequentially using two single optimization problems. Our important and first objective is to minimize the bandwidth. So first we solve for Eq.4.5.1 as a single objective with only one constraint, i.e., Eq.4.5.4. The second optimization problem is solving Eq.4.5.3, using the bandwidth obtained from the first optimization problem. The constraints for the second optimization problem are Eq.4.5.5 to Eq.4.5.9.

4.5.2 Approximate Algorithm for Association of sensors to data collectors

We are given the number of data collectors and their locations. Let's assume the given number of data collectors can handle the load of all the sensors. In the next section, we describe how to handle the load change. If we already have some data collectors, we want to minimize their movement. So the main idea behind the algorithm is to first associate the sensors with more weight with the closest data collector, which in turn reduces the overall distance between the sensors and the data collectors. The first simple approach is, for the given data collector, to keep adding the closest sensor untill its bandwidth limit is reached. The second approach is to use the First-Fit decreasing approach, which gives better results in terms of distance optimization. We have all the information about the items to pack into the bins to design a better approximate algorithm for them. The most successful approximate algorithms are the First-Fit Decreasing and Best-Fit Decreasing methods. First Fit Decreasing uses at most $(4M + 1)/3$ bins if the optimal number is M. So we adopt the First-Fit decreasing method to develop an approximate algorithm. Once we have a sufficient number of data collectors placed in the tracking region, we assign the sensors to the data collectors in decreasing order of their bandwidth. We first order the sensors from largest to smallest weights. For example, suppose the sensor bandwidths are: 56, 45, 37, 25, 16. We first associate the sensor with a bandwidth of 56 with its closest data collector, then the sensor with a bandwidth of 45, and so on. In Algorithm 6, we have described the approximate algorithm for the association of sensors with data collectors.

Algorithm 6 Approximate Algorithm for Association of Sensors to the Data Collectors

Require: Given the number of sensors along with their load, the number of data collectors, and their locations.

Ensure: The Association of sensors to data collectors.

1: Sort the sensors in decreasing order of their load.

2: Mark all sensors as NOT VISITED. `i=1:N`

3: Choose the closest data collector with $B_j >= w_i$

4: Mark s_i as VISITED

5: $B_j \leftarrow$B$_j$ - w_i.

4.5.3 Handling the load change and the new targets

In practical situations, we may have to deal with the new targets at each data collector and its associated sensors. As the new targets are usually not associated with any accuracy requirement until at least a few update times before they are confirmed. We have to compute the bandwidth assignment for these new targets based on the available bandwidth at the data collector and the number of new targets at a given time instance. The number of new targets can change with time in the given tracking region. In general tracking scenarios, most of the new targets enter ROI through the perimeter. So data collectors that are deployed near the perimeter need to have a predefined amount of bandwidth that can be used for the new targets. So the solution can be obtained by solving Eq.4.5.10 . If the load changes, the number of data collectors may also change. For instance, if the load increases due to the addition of new targets or targets from other clusters entered into the given cluster, then the already deployed data collectors may not be enough to collect sufficient data. The question we have to address is how many and where to deploy the extra new data collectors while keeping the already existing ones intact or with little movement. The other possible case is where the load decreases due to probably the targets moving from the given cluster to different clusters, or some targets dying off. The question we have to deal with is how to remove the data collectors that are not required anymore. In case we need fewer data collectors than existing ones, which ones should we keep and which ones should be removed? Algorithm 7, describes the association of sensors to data collectors in the event of a load change.

$$\arg\min_{\mathbf{B}_k^i} \quad \sum_{i=1}^{M} w_i(\mathcal{C}_{\hat{\mathbf{x}}^i_{k|k-1}}\left(B_k^i\right)) \tag{4.5.10}$$

$$\text{s.t.} \sum_{i=1}^{M} \left(B_k^i\right) \leq B_{New} \quad \text{and} \tag{4.5.11}$$

Here, M is the number of new targets, and B_{New} is the total bandwidth availability at the data collector for new targets. Eq.4.5.10 is to minimize the estimation error of the given new targets. The constraint in Eq.4.5.11 is to make sure the total bandwidth, won't exceed the available. The complete end-to-end algorithm is described in Algorithm 8.

Algorithm 7 Algorithm for the association of sensors to data collectors with load change

Require: Given the number of sensors with weights and the existing number of data collectors(k) and their locations.

Ensure: Optimal placement of data collectors and the association of sensors to data collectors.

1: For each cluster, evaluate the bandwidth requirement to achieve the MSE requirement using Eq 4.3.9 to Eq 4.3.11.

2: Compute the number of data collectors(k') required and the initial placement of data collectors using the Algorithm 5.

3: Case1: Where the current data collectors stay at the same place.

Choose the closest existing data collector to each of the newly calculated data collector locations.

4: Case2: Where the current data collectors can move the maximum distance of ($v_{max} * time$) to nearest, best possible location, where v_{max} is the maximum velocity of the given data collector and time is the update time.

For each of the newly calculated data collector positions, select the closest data collector, move it to the new location. $k < k'$

5: Case1: First, associate all possible sensors to existing k data collectors. The remaining $(k' - k)$ data collectors are placed according to Algorithm 5 using not associated sensors.

6: Case2: The remaining $(k' - k)$ number of new data collectors are initially placed at their calculated locations, as in Step 2. $k > k'$

7: The remaining $(k - k')$ data collectors are marked as DELETED.

8: Associate sensors to data collectors using Algorithm 6.

9: All the data collectors are relocated to a weighted centroid location based on all the associated sensors.

Algorithm 8 Algorithm for End-to-End placement of data collectors

Require: Given the number of sensors and accuracy requirements for the targets.

Ensure: Optimal placement of data collectors and the association of sensors to data collectors.

1: Compute the minimum number of data collectors based on the coverage region of data collectors using Eq.4.3.8 .

2: For each cluster, evaluate the bandwidth required to achieve the MSE requirement using Eq 4.3.9 to Eq 4.3.11.

3: Determine the number of data collectors and their locations to deploy by solving Eq 4.4.1 to Eq 4.4.4 or using the approximate Algorithm 5.

4: Add or remove the number of data collectors according to Algorithm 7.

5: Go to step 2, to iteratively relocate the DC to achieve better accuracy and optimal usage of data collectors.

4.6 Coverage Path Planning in case of Fixed Number of data collectors

This section addresses the issue of data gathering that arises when there are fewer data collectors available than needed. Each data collector has to collect the data from more than one group of sensors if the number of groups is greater than the number of data collectors. We can group the sensors based on the load or the coverage radius. We have n data collectors, $DC = \{DC1, DC2, .., DC_n\}$ and m groups or regions, $R = \{R1, R2, ..., R_m\}$ to cover and $m \geq n$. The m regions are partitioned into n sets, and each set is allocated to a unique data collector. Each region has some data to be collected by any one of n data collectors, $D = \{D1, D2, ..., D_m\}$. Let's say the data rate of the data collector i is λ_i and its maximum velocity is v_i. The approach is NP-hard and is comparable to coverage path planning with several data collectors. The goal is to obtain the coverage path with the least amount of coverage time. Different data rates and flying speeds make up the heterogeneous data collectors. The description of the problem is provided after the mathematical formulation, which is given below.

$$\underset{1 \leq i \leq n}{\operatorname{argmin}} \left[\max \sum_{j=0}^{m} \sum_{k=1}^{m} \left(A^i_{j,k} * TT_{i,j,k} + A^i_k * DT_{i,k} \right) \right] \tag{4.6.1}$$

where

$$TT_{i,j,k} = \frac{d_{j,k}}{v_i}, \text{ travel time from } j \text{ to } k \text{ by DC } i \tag{4.6.2}$$

$$DT_{i,k} = \frac{D_k}{\lambda_i}, \text{ data collection time from } k \text{ by DC } i \tag{4.6.3}$$

$$A^i_{j,k} = \begin{cases} 1, & \text{if DC } i \text{ travels from region } j \text{ to } k \\ 0, & \text{otherwise} \end{cases} \tag{4.6.4}$$

$$A^i_k = \begin{cases} 1, & \text{if DC } i \text{ collects the data from region } k0, \\ \text{otherwise} & \end{cases} \tag{4.6.5}$$

Subject to

$$\text{C1:} \sum_{j=1}^{m} A_{0,j}^{i} = 1 \quad \forall i \in n \tag{4.6.6}$$

$$\text{C2:} \sum_{j=1}^{m} A_{j,f}^{i} = 1 \quad \forall i \in n \tag{4.6.7}$$

$$\text{C3:} \sum_{j=1}^{m} \sum_{i=1}^{n} A_{k,j}^{i} = 1 \quad \forall k \in m \tag{4.6.8}$$

$$\text{C4:} \sum_{k=1}^{m} \sum_{i=1}^{n} A_{k,j}^{i} = 1 \quad \forall j \in m \tag{4.6.9}$$

$$\text{C5:} \sum_{i=1}^{n} A_{j}^{i} = 1 \quad \forall j \in m \tag{4.6.10}$$

The meaning of each constraint is given below.

C1: All the data collectors can start from the same point or from different points. If all the data collectors start from the same location, the maximum number of data collectors leaving from the start point is n. If the start point is different, then only one data collector can leave from each start point.

C2: Either the same point or a different point can be reached by all data collectors. The greatest number of data collectors that can travel to the completion point is n if all data collectors finish in one place. There can only be one data collector per finish point if the finish points are different.

C3, C4: Any point should only have one edge connecting it to it. This implies that just one data collector will arrive at each point, and that only one data collector will depart from each point.

C5: Each region's data is collected by a single data collector.

$A^i_{j,k}$ is a boolean variable to indicate whether the data collector i travelled from group j to k. Another boolean variable, $A_k i$, is used to indicate if the data collector i collects data from the region k. $A^i_{0,j}$ denotes the start point, for the data collector, i, and reaching to region j. If the regions are dispersed over the tracking region, it is more advantageous if the start points are different. As data collection is a continuous process, we can have separate finish points for each data collector, or the finish points can be near the last coverage region. $A^i_{j,f}$ indicates the finish point for data collector i from region j. The start and finish points can coincide in some circumstances. $d_{j,k}$ is the Euclidean distance between the regions j, k The total time consumed by each data collector is divided into two parts. The first part is travel time (TT) by the data collector to a given region in a set, which is derived by Eq.4.6.2. The second part is the data collection time (DT) for a given region, which is given in Eq.4.6.3. The time it took for all data collectors to finish the coverage mission was the longest total data collector's time in this path planning challenge. The total time of each data collector should be as close to equal as feasible when regions are assigned to the data collectors, which gives the best possible minimum coverage time.

4.6.1 Methodology

When attempting to solve the coverage path planning issue, we use the parameter known as minimum total time (MTT) to solve the coverage path planning optimization problem. MTT is a summation of travel time and data collection time. The data collectors can start at the same location or at different locations. The details of the algorithm are given in Algorithm 9. Our first goal is to group the m regions into n sets. As an initial step, select the closest region for each data collector. Set S_j represents the set of all regions that are going to be covered by the data collector j. It is a crucial step in how we compute the next region for the given set. We compute all possible total times for the set of regions in S_j to all the unassigned regions. Select the path from q to k ($R_q \rightarrow R_k$) which gives the MTT, and add the region k into the set S_j. The next step is to find the short path for the data collector to travel using any method similar to the travel salesman problem (TSP) using a single data collector. For simplicity, we use the nearest neighbour solution to find the minimal travel path in each set.

Algorithm 9 Pseudocode for Minimum Total Time Algorithm

Require: Given the number of regions, each with a unique centroid location, and the number and location of data collectors.

Ensure: Set of regions is assigned to each data collector.

1: Set $time[n] \leftarrow 0$, for all n data collectors.

2: Set $S_n \leftarrow null$ for all n data collectors.

3: Select the closest region for each data collector.

4: Mark all regions, R_m, as unassigned.

5: Put the closest region to each data collector, in the set S_n and mark them as assigned. There exists an unassigned region

6: Sort times in ascending order.

7: Choose the data collector, j with the minimum total time.

8: Find a region k that is unassigned and gives the minimum increase in total time from the region q which is in the set S_j. $\min\{(time(j) + tt_{R_q \rightarrow R_k})\}$ where $tt_{R_q \rightarrow R_k}$ is the total time for the data collector j to travel from R_q to and R_k and data collection from R_k

9: Update $time(j) = time(j) + tt_{R_q \rightarrow R_k}$

10: Mark region k as assigned

11: Update $S_j \leftarrow S_j + R_k$ `j=1:n`

12: Find the travel path for the data collector j using the nearest neighbour algorithm for the regions in the set S_j.

4.7 Performance Analysis

Given the tracking region with the given number of sensors, as shown in Fig.4.2. These sensors are associated with a certain number of targets with a given required performance. Our aim is to determine the number of required data collectors to be deployed to meet the given accuracy requirement. The first problem to solve is to

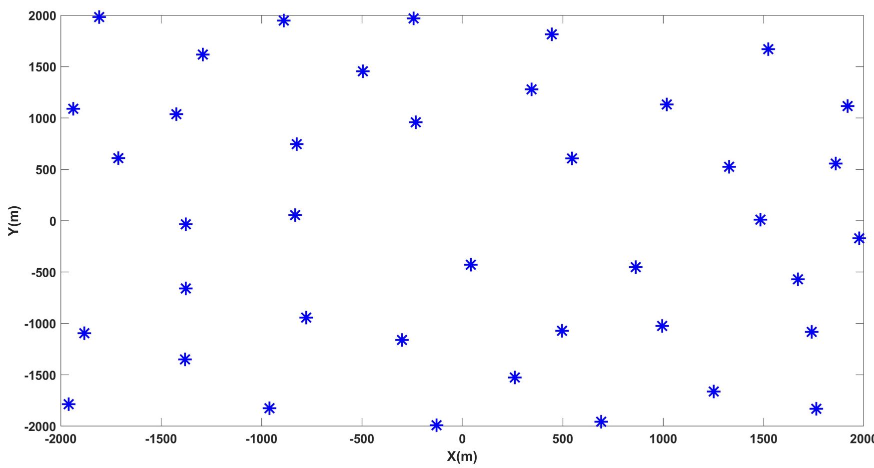


Figure 4.2: Sensors in the Tracking Region

form the clusters based on the available data collectors' coverage radii. Then compute the centroid location. In Fig.4.3, we showed the clusters with associated sensors. At least one data collector is placed in each cluster to cover all the sensors in the region. The sensors in Fig.4.2 are formed into 5 clusters using a coverage radius of 1300. The sensor of the same colour represents the cluster of sensors. We assumed all the data collectors were within the same coverage radius. The centroid locations are shown in Fig.4.4. For each sensor, calculate the bandwidth requirement based on the number of targets and their accuracy requirements. Initially, to get information on the number of targets and their accuracy, one data collector is placed at the centroid location.

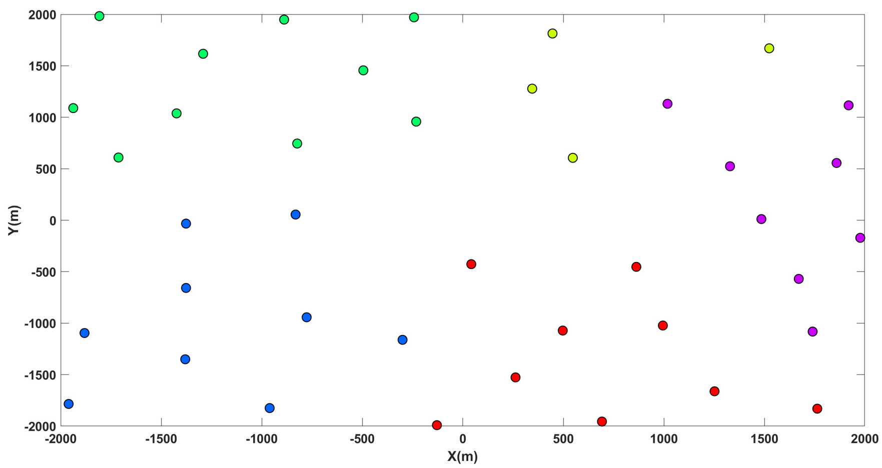


Figure 4.3: Clusters Formation

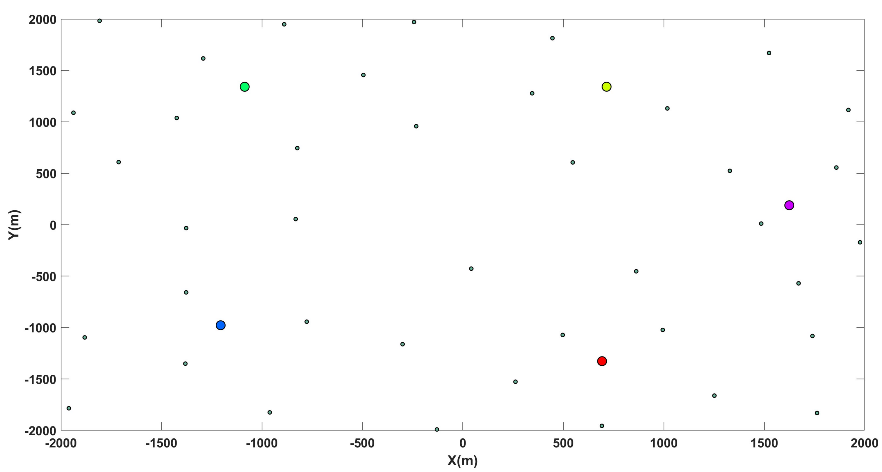


Figure 4.4: Centroid Location

Fig.4.5, shows the relationship between accuracy and the bit requirement. If we need

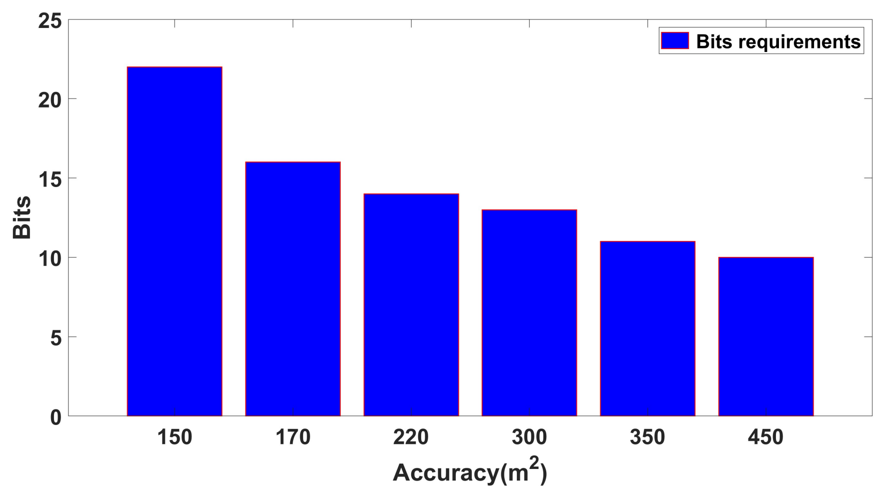


Figure 4.5: Relationship between accuracy and bit requirement

good accuracy in terms of MSE, we need to allocate more bits. The number of bits depends on several factors, which include sensor characteristics, the location, and the direction of the target. As a result, accuracy and bit requirements are inversely proportional. In Fig.4.6, we have 40 sensors, and the bandwidth requirement is shown at each sensor node. We assume each data collector can handle 200 bandwidth. Using the initial placement algorithm, we needed seven data collectors, and their initial associations are shown in different colour codes. We can apply the initial placement algorithm over the region of interest or within one cluster if there are more sensors. We can get better performance in terms of the number of data collectors to be deployed at the cost of time to compute the initial placement locations.

In the next scenario in Fig.4.7, we have 5 sensors, and each has one or more targets. In this case, we've demonstrated how data collectors are relocated following the assignment process and how sensors are connected to them. For this given scenario, S1, S2, and S3 are associated with DC1 and relocated in the direction of the arrow.

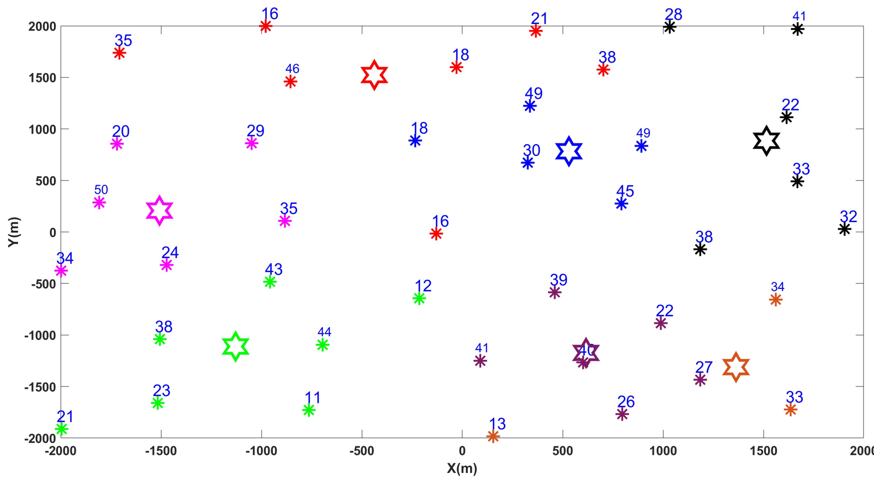


Figure 4.6: Initial Placement of Data Collectors

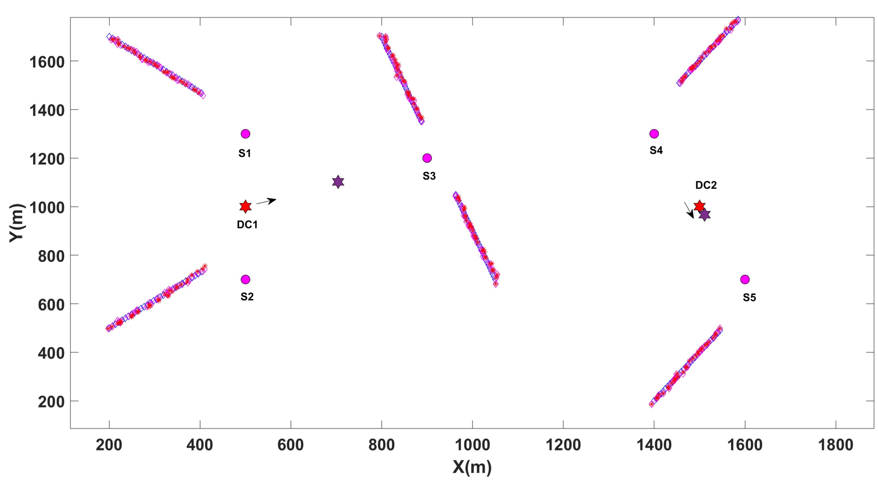


Figure 4.7: Sensors assignment to Data Collectors

S4 and S5 are associated with DC2. Targets T1, T2, T5, and T6 are being tracked by S1, S2, S4, and S5, respectively. T3 and T4 are tracked by S3. Each target has a target accuracy of [150, 200, 200, 250, 350, 150]. In Fig.4.8, we have shown how

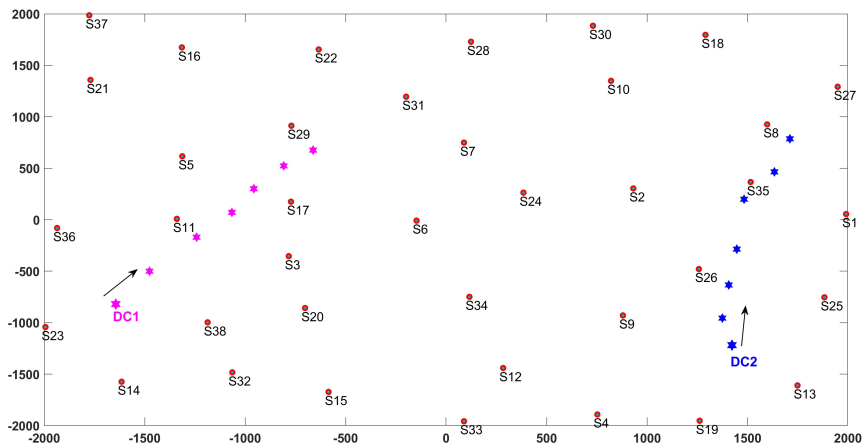


Figure 4.8: Data collector Movement along with the load

the data collectors move along with the load. Each time, the load is moving in the direction of the arrow. In this scenario, we have two data collectors and a total of 40 sensors. As the targets are moving in one direction, the data collectors are being relocated toward the load shift. We assume the bandwidth availability at each data collector is 500. Tables 1 and 2 show the load change at the sensors. The bandwidth requirement for the other sensors, which are not listed in the tables, is zero. The time interval depends on the tracking scenario and how fast the targets can move from one sensor to the next. For fast-moving targets, the time interval is small, and for slow-moving targets, the time interval can be large.

In the next experiment, we will illustrate how the number of data collectors required can change with load. In Fig.4.9, we have 40 sensors, each associated with

Table 4.1: Load change at data collector 1

time1	**time2**	**time3**	**time4**	**time5**	**time6**	**time7**
S23: 100	S23: 50	S36: 50	S29: 50	S29: 100	S5: 100	S5: 50
S36: 100	S36: 100	S11: 100	S11: 100	S11: 50	S29: 100	S29: 100
S11: 50	S11: 50	S38: 100	S38: 50	S3: 100	S3: 50	S22: 100
S14: 100	S14: 50	S3: 100	S3: 100	S5: 100	S17: 100	S17: 100
S38: 100	S38: 100	S5: 100	S5: 100	S17:100	S6: 50	S6: 100
S17: 0	S3: 50	S23: 0	S23: 0	S38: 0	S22: 50	S11: 0
S5: 0	S5: 50	S17: 0	S17: 50	S36: 0	S22: 0	S3: 0

Table 4.2: Load change at data collector 2

time1	**time2**	**time3**	**time4**	**time5**	**time6**	**time7**
S9: 100	S9: 50	S9: 0	S19: 50	S19: 0	S8: 50	S2: 0
S19: 100	S19: 100	S19: 100	S2: 100	S2: 100	S2: 50	S35: 100
S2: 0	S2: 50	S2: 100	S35: 50	S35: 100	S35: 100	S8: 100
S13: 100	S13: 50	S13: 0	S13: 0	S25: 0	S25: 0	S26: 0
S25: 100	S25: 100	S25: 100	S25: 50	S26: 100	S26: 50	S1: 100
S26: 50	S26: 100	S26: 100	S26: 100	S1: 100	S1: 100	S27: 100
S1: 0	S1: 0	S1 : 50	S1: 100	S27: 50	S27: 100	S18: 50

calculated bandwidth requirements similar to Fig.4.6. Each data collector's bandwidth capacity is 200. We compute the number of data collectors required and do the initial placement. Then we associate the sensors to the data collectors using the approximate association Algorithm 6. The sensors are associated with the seven data collectors that we have deployed, and they are represented by various colour codes. The load at 20 sensors was increased in Fig.4.10. The number of data collectors and their locations were subsequently recalculated. To fulfill the need, two more data collectors are needed. We can set up the additional data collectors in one of two ways. In the first case, we keep the data collectors as they are and then compute the locations for the new data collectors. The additional deployed data collectors are shown in the green circles in Fig.4.10 and do the association. In the second case, the

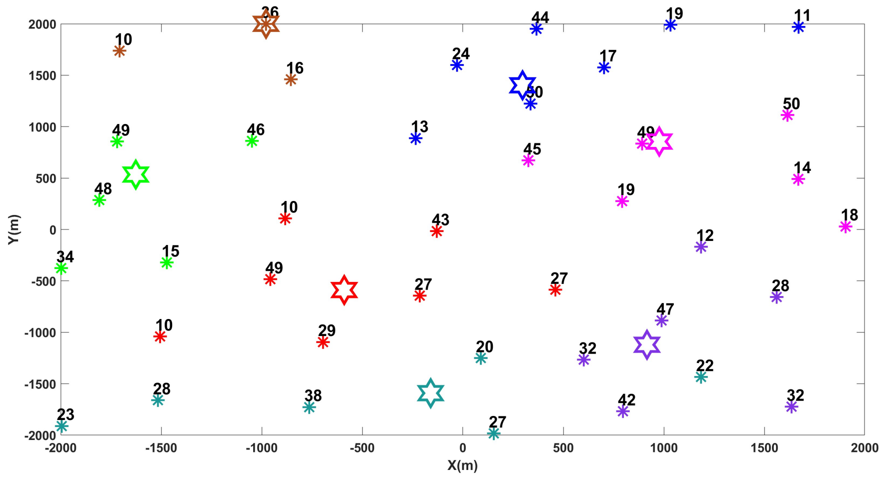


Figure 4.9: Association of sensors to the Data Collectors

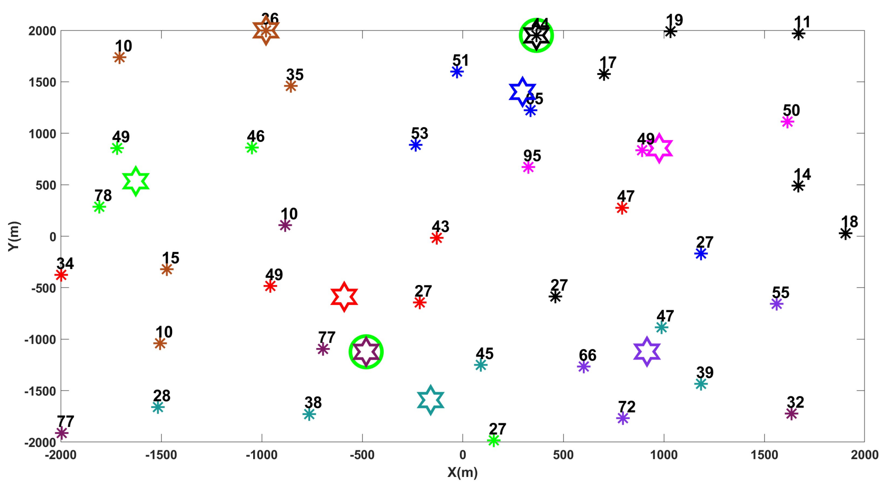


Figure 4.10: Case1: Additional Deployment of the Data Collectors without changing the original Data Collectors

data collectors are moved to the best possible locations nearby, and then the location is computed for the new data collectors. The new placement is shown in Fig.4.11 for case2. The main advantage of this case is that sometimes we may need fewer data collectors than in case 1. In Fig.4.12, we decreased the load at all sensors. Then

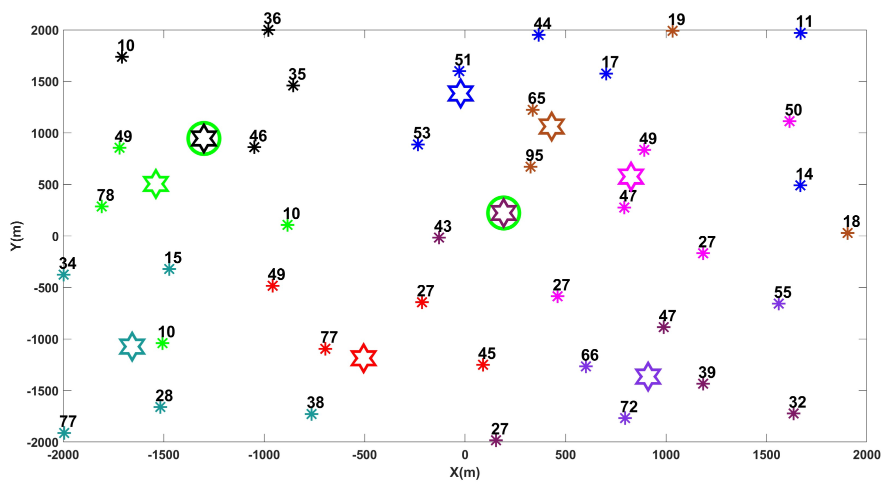


Figure 4.11: Case2: Additional Deployment of the data collectors, by moving the original data collectors

we recomputed the number of sensors and their locations. To handle the load, just five data collectors were required. Hence, one data collector that is to be removed is indicated in the red circle, and do the association.

We compare the approximate initial placement algorithm with the optimal solution to two simple scenarios using a Genetic Algorithm implemented in MATLAB. We have two scenarios, each of which has a different load at each sensor. In case1, we have 7 sensors with the load {20, 50, 40, 70, 10, 30, 80} respectively, for the first case, as shown in Fig4.13. The capacity of each available data collector is 100. We required three data collectors in order to acquire the optimal distribution, and we

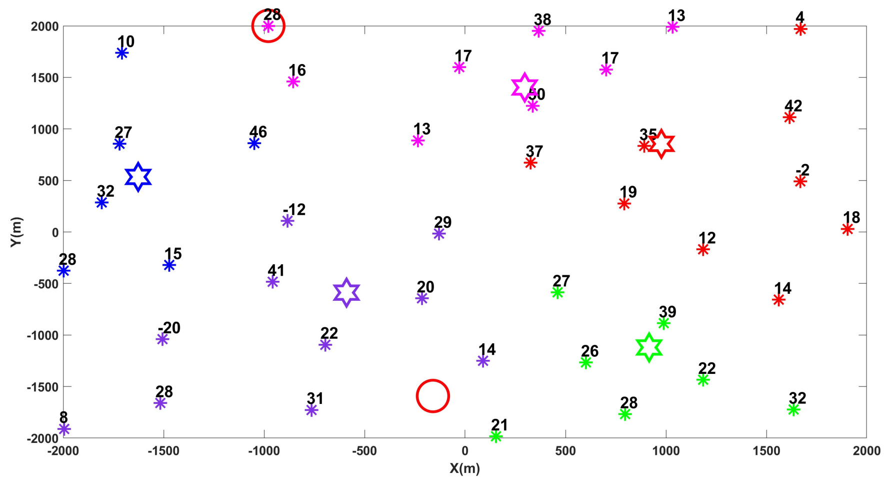


Figure 4.12: Data collector removal due to load decrement

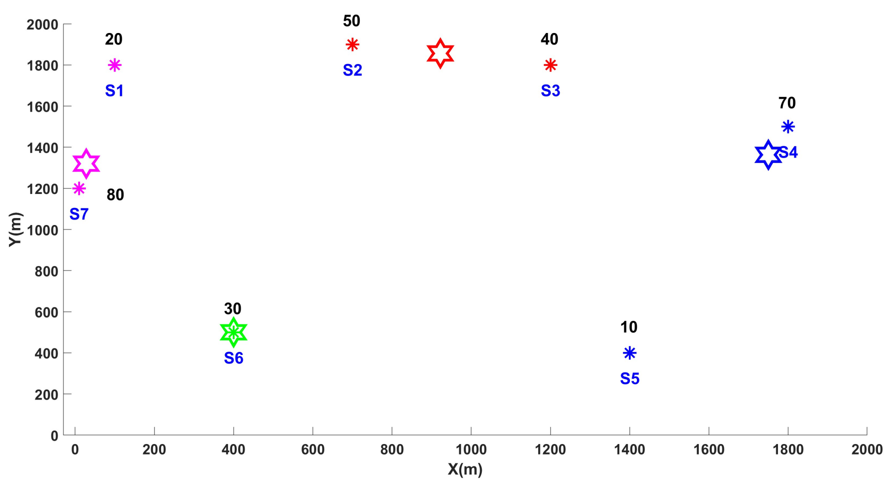


Figure 4.13: Case1: Comparison with an Optimal Scenario

obtained them using the MATLAB-implemented GA algorithm. However, the approximate initial placement algorithm gives one more extra-data collector than the optimal number of data collectors.

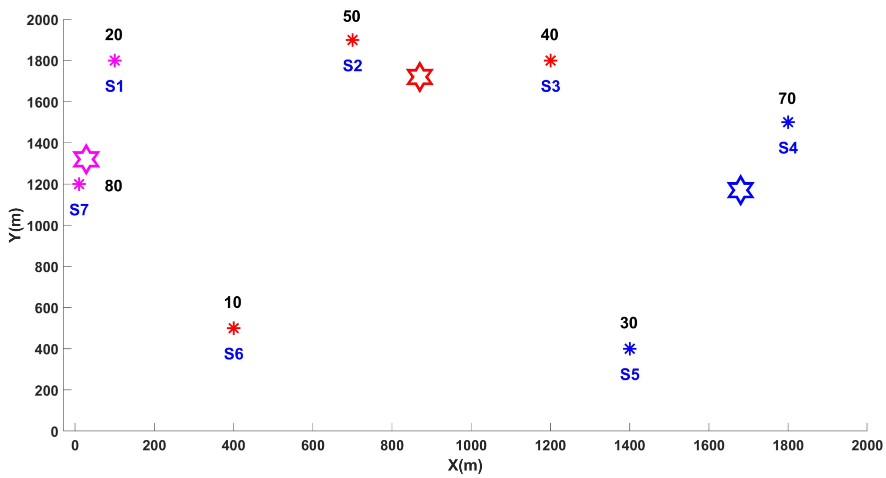


Figure 4.14: Case2: Comparison with Optimal Scenario

In the second case, the sensors have loads {20, 50, 40, 70, 30, 10, and 80} as shown in Fig.4.14. The approximate algorithm exactly gives the optimal number of data collectors, which is three. The main difference between cases 1 and 2 is the load swap at S5 and S6. So, in scenario 1, S5 has a load of 10, while S6 has a load of 30. S5 and S6 in case 2 each have 30 and 10, respectively. So in summary, the number of data collectors that are computed based on the approximate algorithms depends on the location of the data collectors as well as their load distribution. The detailed comparison between the Genetic Algorithm (GA) implemented in MATLAB and the approximate algorithm is provided in Table.4.3 The distance parameter in the Table-III is the total distance between the centroid and the associated sensors for all regions. The time of computation is very large for GA compared to the approximate algorithm. So there is a trade-off between the number of data collectors and the total distance between the centroid and the associated sensors. As it is more expensive to install a new data collector, having the fewest possible data collectors in a real-time environment is more important than minimizing the distance.

Table 4.3: Comparison of Genetic Algorithm(GA) Algorithm and Proposed Approximate Algorithm

	Genetic Algorithm		**Approximate Algorithm**	
Parameter	Case1	Case2	Case1	Case2
Time(s)	5.3725	5.1704	0.033320	0.020650
Distance(m)	4.3971e+03	3.6717e+03	2.2871e+03	3.6717e+03
No.of DCs	3	3	4	3

The performance of the MTT coverage path planning algorithm is examined in the following experiment. We have only three data collectors and 13 regions to collect the data. Initially, three data collectors are stationed in different locations. The details are shown in Fig.4.15. Each region has a set of sensors with some data to communicate to the data collector. The data collectors gather data from each region's centroid location, which is indicated by a star. The maximum flight speeds for data collectors DC1, DC2, and DC3 are 40, 50, and 46 m/s, respectively. The data rate is 500 bits/sec for all the data collectors. The data in each region varies from [1000, 1200]. The region allocation using the MTT is shown in Fig.4.15. The total travel time for each data collector using MTT approximation is [174.4627, 174.7184, 177.1049] for DC1, DC2, and DC3, respectively. Each data collector's set coverage is displayed using a separate colour scheme. We contrast the outcomes of the suggested MTT algorithm with those of two different approximations. Based on distance, is the first one. We select the region that is the next closest to the current region. The second

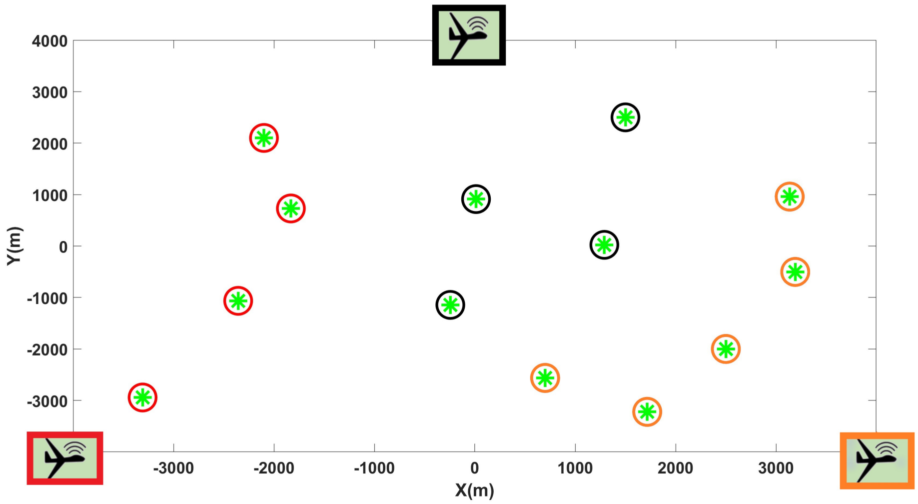


Figure 4.15: Coverage Path Planning using Minimum Total Time

one is determined by the minimum travel time to data transfer time ratio (MTD). The logical choice is to move on to the next region that requires less travel time than data transfer time. The region allocations to data collectors using the shortest distance and MTD are shown in Fig.4.16 and Fig.4.17. For the first data collector in red colour, the region allocation is the same for all three algorithms. However, there are differences in the allocation for the second data collector, which is orange, and the third data collector, which is in colour black. When compared to the approximation of the shortest distance, MTT and MTD performed well in terms of time.

We compare the total time for all three data collectors using three algorithms in Fig.4.18.

4.8 Conclusion

In this paper, we addressed the important question of the number of data collectors to deploy in the given tracking region of interest and how to associate them with the

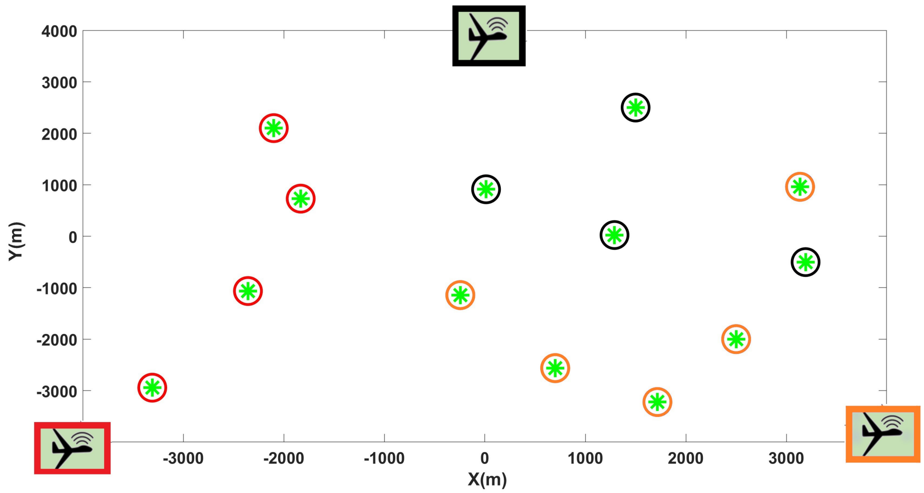


Figure 4.16: Coverage Path Planning using the Shortest Distance

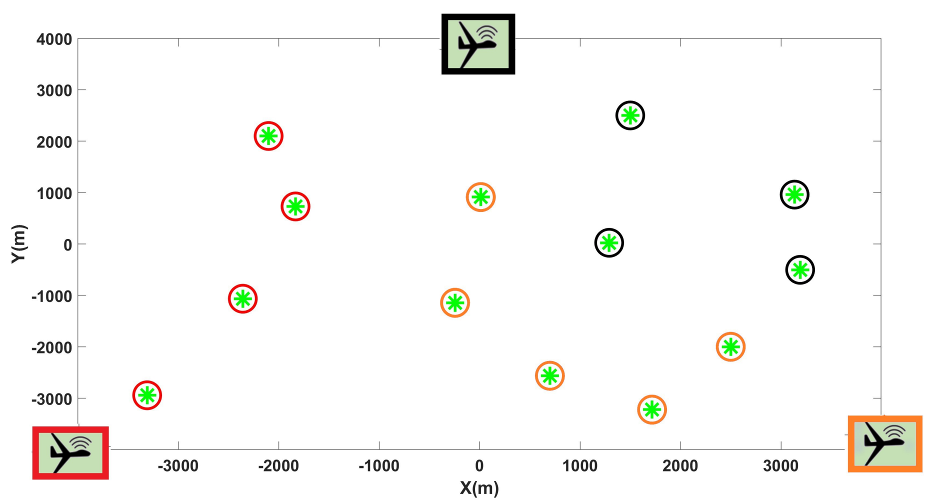


Figure 4.17: Coverage Path Planning using MTD

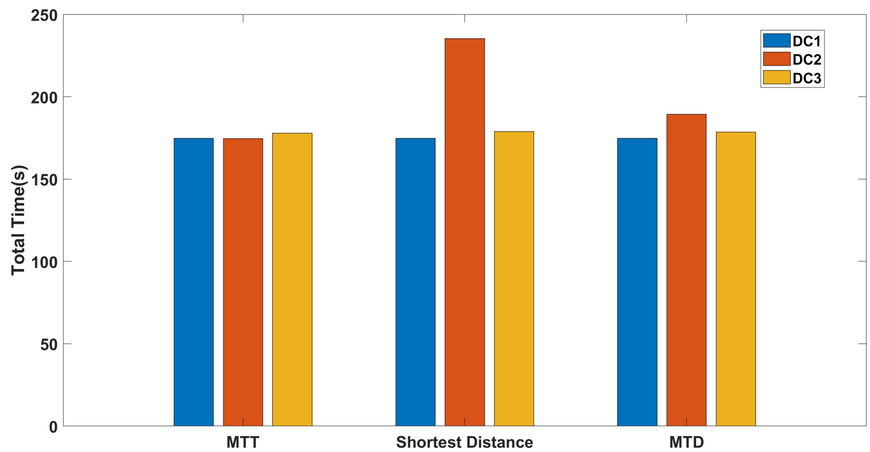


Figure 4.18: Total Time Comparison for three Data Collectors

sensors. We first compute the load requirement at each sensor node using the number of targets and their accuracies. Then, based on the bit requirement at each sensor node, we calculate the number of data collectors required. We modelled the initial placement of data collectors using the given load at each sensor node, which is similar to the bin packing algorithm. We proposed a novel method to adaptively relocate the data collectors as the load changes at each sensor node. We formulated the problem of associating sensors to a data collector as a Multi-objective problem, where one sensor is assigned to only one data collector. We proposed an approximate, suboptimal algorithm for the initial location and number of data collectors. The Multi-Objective Optimization problem was solved using the lexicographic approach, which successfully generates the best solution by outlining the sequential optimization stages. In the event of a fixed number of available data collectors, we tackled the coverage path planning problem. To solve the coverage path planning problem, we presented a suboptimal approximation algorithm, and compared the outcomes with those of two other techniques. The simulation results illustrate the effectiveness and performance benefits of the proposed approaches. When we contrast the approximation method with the ideal outcomes, the findings are fairly close to the ideal solution. In further work, we will incorporate additional data collection capabilities, such as acceleration, turn rate, and minimum speed, as well as other pertinent features, into the formulas. While moving the data collector, we will also take into account the ideal time to estimate the targets' states.

Chapter 5

Conclusions and Future Works

5.1 Conclusions

This thesis studied the design of algorithms to associate sensor nodes to fusion centers using quantized measurements. For multi-target tracking, the dynamic bit allocation problem was taken into account. The task was described as a multi-objective integer optimization problem that minimizes the PCRLB and maximizes resource usage under bandwidth and energy restrictions. By taking into account the target trajectory and sensor properties, our method distributes the bits for each target as well as inside the measurement vector. We took tentative tracks into account when prioritizing the tracks in SROI for quick initialization. Two optimization issues were separated from the original one. The initial optimization task at the FC was to distribute the bits to all tracks based on PCRLB while taking into account the available bits at the FC and each sensor node. The second optimization challenge was to manage mis-detections and redistribute the additional available bits to tracks that maximize the Fisher information at the local sensor node. With the use of static bit allocation, we provided an approximation of an algorithm that determines each track's priority and weight based on the contribution of FI. The simulation results showed that the suggested techniques were more successful than fixed or static bit allocation.

We proposed a novel approach for assigning targets to fusion centers and allocating bandwidth jointly for multi-target tracking in various distributed radar networks against a cluttered background. In resource-constrained scenarios, the goal was to gather the best sensor data for each target to increase tracking performance and make the greatest use of the energy available at sensor nodes and fusion centers. We tackled the issue of associating the targets to fusion centers and effectively allocating the bandwidth to the targets in order to enhance tracking performance and extend the lifespan of each fusion center as well as sensor nodes through efficient energy use. In the first stage, we associated the targets with the fusion centers. The next step was to assign the bandwidth to targets at each of the sensors. To reduce communication costs, we moved the fusion centers to the centroid location in the third stage. For the multi-objective integer optimization issue, we suggested a technique for generating initial values. Two approximate bandwidth distribution techniques that deliver nearly perfect results more quickly were proposed. We tackled the crucial issue of how many data collectors should be placed in the specified tracking region of interest, as well as how to connect them to the sensors. We initially used the number of targets and their accuracy to calculate the load needed at each sensor node. Then, we determined the necessary number of data collectors based on the bit requirements at each sensor node. Using the available load at each sensor node, we modelled the initial placement of data collectors in a manner similar to the bin packing problem. We suggested a novel technique to move the data collectors when the load varies at each sensor node.

One sensor is assigned to just one data collector in our multi-objective formulation of the issue of connecting sensors to data collectors. For the initial placement and quantity of data collectors, we suggested a roughly suboptimal algorithm. The lexicographic approach, which successfully develops the optimal solution by sketching the sequential optimization steps, was used to solve the multi-objective optimization issue. We took on the challenge of coverage path planning when there were only a fixed number of data collectors available. We introduced a suboptimal approximation algorithm to address the coverage path planning problem, and we contrasted the results with two other approaches.

5.2 Future Works

First and foremost, the communication between sensor nodes is not taken into account in this work. However, it is likely that when the additional communication component is taken into consideration, all the developed algorithms will perform better. Next, only standard sensor characteristics are considered in this work. Modern sensor capabilities could be incorporated into the framework. For instance, properties of image and optical sensors. In addition to the data collectors' already-existing capabilities, there is a chance to include in the formulation other data-gathering capabilities like acceleration, turn rate, and minimum speed. Better bit allocation results from including additional target properties in the formulation, such as maneuverable behaviours. The relationship between the update time and the bare minimum number of data collectors needed is not discussed in this study. The assumption is made that the update time is greater than the data collection time using the given number of data collectors. This assumption might not hold true in some situations, especially if the update time is either short or extremely long. Additionally, we assumed that all the sensors' update times would be the same. In order to accept sensors with various update rates, more research is needed. We considered only single-hop communication between the sensor node and the fusion center. The problem can be extended to include multi-hop communication where a fusion center can not reach some sensor nodes. We assumed the measurement noise was uncorrelated among sensors. However, the measurement noises are probably associated with two sensors that are close to one another. To overcome these difficulties, additional research on this issue is required. The proposed approximate algorithms are suboptimal. To further increase algorithm efficiency, more effective solutions must be investigated to fill the optimality gap and create substitute optimization strategies.

Bibliography

[1] A. Ababneh. Low-complexity bit allocation for rss target localization. *IEEE Sensors Journal*, 19(17):7733–7743, 2019.

[2] B. Allik, M. J. Piovoso, and R. Zurakowski. Recursive estimation with quantized and censored measurements. In *2016 American Control Conference (ACC)*, pages 5130–5135. IEEE, 2016.

[3] M. Alzenad, A. El-Keyi, F. Lagum, and H. Yanikomeroglu. 3-d placement of an unmanned aerial vehicle base station (uav-bs) for energy-efficient maximal coverage. *IEEE Wireless Communications Letters*, 6(4):434–437, 2017.

[4] Y. Bar-Shalom and X.-R. Li. *Multitarget-multisensor tracking: principles and techniques*, volume 19. YBs Storrs, CT, 1995.

[5] S. Blackman and R. Popoli. Design and analysis of modern tracking systems(book). *Norwood, MA: Artech House, 1999.*, 1999.

[6] R. I. Bor-Yaliniz, A. El-Keyi, and H. Yanikomeroglu. Efficient 3-d placement of an aerial base station in next generation cellular networks. In *2016 IEEE International Conference on Communications (ICC)*, pages 1–5, 2016. doi: 10.1109/ICC.2016.7510820.

[7] R. I. Bor-Yaliniz, A. El-Keyi, and H. Yanikomeroglu. Efficient 3-d placement of an aerial base station in next generation cellular networks. In *2016 IEEE international conference on communications (ICC)*, pages 1–5. IEEE, 2016.

[8] P. Braca, M. Guerriero, S. Marano, V. Matta, and P. Willett. Distributed estimation with data association: Is the nearest neighbor the most informative? In *2009 12th International Conference on Information Fusion*, pages 780–785. IEEE, 2009.

[9] P. Braca, M. Guerriero, S. Marano, V. Matta, and P. Willett. Selective measurement transmission in distributed estimation with data association. *IEEE Transactions on Signal Processing*, 58(8):4311–4321, 2010.

[10] P. Braca, R. Goldhahn, G. Ferri, and K. D. LePage. Distributed information fusion in multistatic sensor networks for underwater surveillance. *IEEE Sensors Journal*, 16(11):4003–4014, 2016.

[11] N. Cao, S. Choi, E. Masazade, and P. K. Varshney. Sensor selection for target tracking in wireless sensor networks with uncertainty. *IEEE Transactions on Signal Processing*, 64(20):5191–5204, 2016.

[12] S. Chandrasekharan, K. Gomez, A. Al-Hourani, S. Kandeepan, T. Rasheed, L. Goratti, L. Reynaud, D. Grace, I. Bucaille, T. Wirth, et al. Designing and implementing future aerial communication networks. *IEEE Communications Magazine*, 54(5):26–34, 2016.

[13] J. Chen, C. Du, Y. Zhang, P. Han, and W. Wei. A clustering-based coverage path planning method for autonomous heterogeneous uavs. *IEEE Transactions*

on Intelligent Transportation Systems, 23(12):25546–25556, 2022. doi: 10.1109/TITS.2021.3066240.

[14] J. Chen, Y. Zhang, L. Wu, T. You, and X. Ning. An adaptive clustering-based algorithm for automatic path planning of heterogeneous uavs. *IEEE Transactions on Intelligent Transportation Systems*, 23(9):16842–16853, 2022. doi: 10.1109/TITS.2021.3131473.

[15] K. Clements and R. Haddad. Approximate estimation for systems with quantized data. *IEEE Transactions on Automatic Control*, 17(2):235–239, 1972.

[16] R. Curry, W. Velde, and J. Potter. Nonlinear estimation with quantized measurements–pcm, predictive quantization, and data compression. *IEEE Transactions on Information Theory*, 16(2):152–161, 1970.

[17] R. E. Curry. *Estimation and control with quantized measurements*. MIT press, 1970.

[18] M. Di Francesco, S. K. Das, and G. Anastasi. Data collection in wireless sensor networks with mobile elements: A survey. *ACM Transactions on Sensor Networks (TOSN)*, 8(1):1–31, 2011.

[19] Z. Duan, V. P. Jilkov, and X. R. Li. Posterior cramer-rao bounds for state estimation with quantized measurement. pages 376–380, 2008.

[20] Z. Duan, V. P. Jilkov, and X. R. Li. State estimation with quantized measurements: Approximate mmse approach. In *2008 11th International Conference on Information Fusion*, pages 1–6. IEEE, 2008.

[21] H. Ergezer and K. Leblebicioglu. Path planning for uavs for maximum information collection. *IEEE Transactions on Aerospace and Electronic Systems*, 49(1): 502–520, 2013.

[22] N. Garcia, A. M. Haimovich, M. Coulon, and M. Lops. Resource allocation in mimo radar with multiple targets for non-coherent localization. *IEEE Transactions on Signal Processing*, 62(10):2656–2666, 2014. doi: 10.1109/TSP.2014.2315169.

[23] N. Garcia, A. M. Haimovich, M. Coulon, and M. Lops. Resource allocation in mimo radar with multiple targets for non-coherent localization. *IEEE Transactions on Signal Processing*, 62(10):2656–2666, 2014.

[24] O. Ghdiri, W. Jaafar, S. Alfattani, J. B. Abderrazak, and H. Yanikomeroglu. Energy-efficient multi-uav data collection for iot networks with time deadlines. In *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, pages 1–6, 2020. doi: 10.1109/GLOBECOM42002.2020.9322626.

[25] M. B. Ghorbel, D. Rodríguez-Duarte, H. Ghazzai, M. J. Hossain, and H. Menouar. Joint position and travel path optimization for energy efficient wireless data gathering using unmanned aerial vehicles. *IEEE Transactions on Vehicular Technology*, 68(3):2165–2175, 2019. doi: 10.1109/TVT.2019.2893374.

[26] H. Gish and J. Pierce. Asymptotically efficient quantizing. *IEEE Transactions on Information Theory*, 14(5):676–683, 1968.

[27] H. Godrich, A. P. Petropulu, and H. V. Poor. Power allocation strategies for target localization in distributed multiple-radar architectures. *IEEE Transactions on Signal Processing*, 59(7):3226–3240, 2011. doi: 10.1109/TSP.2011.2144976.

[28] H. Godrich, A. P. Petropulu, and H. V. Poor. Power allocation strategies for target localization in distributed multiple-radar architectures. *IEEE Transactions on Signal Processing*, 59(7):3226–3240, 2011.

[29] H. Godrich, A. P. Petropulu, and H. V. Poor. Sensor selection in distributed multiple-radar architectures for localization: A knapsack problem formulation. *IEEE Transactions on Signal Processing*, 60(1):247–260, 2011.

[30] B. K. Habtemariam, A. Aravinthan, R. Tharmarasa, K. Punithakumar, T. Lang, and T. Kirubarajan. Distributed tracking with a phd filter using efficient measurement encoding. *J. Adv. Inf. Fusion*, 7(2):114–130, 2012.

[31] M. Huang and S. Dey. Dynamic quantizer design for hidden markov state estimation via multiple sensors with fusion center feedback. *IEEE Transactions on Signal Processing*, 54(8):2887–2896, 2006.

[32] F. Jiang and A. L. Swindlehurst. Optimization of uav heading for the ground-to-air uplink. *IEEE Journal on Selected Areas in Communications*, 30(5):993–1005, 2012. doi: 10.1109/JSAC.2012.120614.

[33] S. Karimi-Bidhendi, J. Guo, and H. Jafarkhani. Energy-efficient node deployment in heterogeneous two-tier wireless sensor networks with limited communication range. *IEEE Transactions on Wireless Communications*, 20(1):40–55, 2021. doi: 10.1109/TWC.2020.3023065.

[34] E. Koyuncu, M. Shabanighazikelayeh, and H. Seferoglu. Deployment and trajectory optimization of uavs: A quantization theory approach. *IEEE Transactions on Wireless Communications*, 17(12):8531–8546, 2018.

[35] M. Le Berre, F. Hnaien, and H. Snoussi. Multi-objective optimization in wireless sensors networks. In *ICM 2011 Proceeding*, pages 1–4, 2011. doi: 10.1109/ICM.2011.6177401.

[36] J. Liu, P. Tong, X. Wang, B. Bai, and H. Dai. Uav-aided data collection for information freshness in wireless sensor networks. *IEEE Transactions on Wireless Communications*, 20(4):2368–2382, 2021. doi: 10.1109/TWC.2020.3041750.

[37] S. Liu, S. P. Chepuri, M. Fardad, E. Maşazade, G. Leus, and P. K. Varshney. Sensor selection for estimation with correlated measurement noise. *IEEE Transactions on Signal Processing*, 64(13):3509–3522, 2016.

[38] S. Liu, Z. Wei, Z. Guo, X. Yuan, and Z. Feng. Performance analysis of uavs assisted data collection in wireless sensor network. In *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, pages 1–5. IEEE, 2018.

[39] X. Luo and G. B. Giannakis. Energy-constrained optimal quantization for wireless sensor networks. *EURASIP Journal on Advances in Signal Processing*, 2008 (1):462930, 2007.

[40] J. Lyu, Y. Zeng, R. Zhang, and T. J. Lim. Placement optimization of uav-mounted mobile base stations. *IEEE Communications Letters*, 21(3):604–607, 2016.

[41] M. Mansouri, H. Snoussi, and C. Richard. Joint adaptive quantization and fading channel estimation for target tracking in wireless sensor networks. In *2009 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, pages 612–615. IEEE, 2009.

[42] S. Marano, V. Matta, and P. Willett. Some approaches to quantization for distributed estimation with data association. *IEEE transactions on signal processing*, 53(3):885–895, 2005.

[43] E. Masazade and P. K. Varshney. A market based dynamic bit allocation scheme for target tracking in wireless sensor networks. In *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 4207–4211, 2013. doi: 10.1109/ICASSP.2013.6638452.

[44] E. Masazade, R. Niu, P. K. Varshney, and M. Keskinoz. Energy aware iterative source localization for wireless sensor networks. *IEEE Transactions on Signal Processing*, 58(9):4824–4835, 2010.

[45] E. Masazade, R. Niu, and P. K. Varshney. Dynamic bandwidth allocation for target tracking in wireless sensor networks. In *14th International Conference on Information Fusion*, pages 1–8. IEEE, 2011.

[46] E. Masazade, R. Niu, and P. K. Varshney. Dynamic bit allocation for object tracking in bandwidth limited sensor networks. *arXiv preprint arXiv:1110.5342*, 2011.

[47] E. Masazade, R. Niu, and P. Varshney. Dynamic bit allocation for object tracking in wireless sensor networks. volume 60, pages 5048–5063. IEEE, 2012.

[48] E. Masazade, R. Niu, and P. K. Varshney. Dynamic bit allocation for object tracking in wireless sensor networks. *IEEE Transactions on Signal Processing*, 60(10):5048–5063, 2012. doi: 10.1109/TSP.2012.2204257.

[49] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage. *IEEE Communications Letters*, 20(8):1647–1650, 2016. doi: 10.1109/LCOMM.2016.2578312.

[50] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage. *IEEE Communications Letters*, 20(8):1647–1650, 2016.

[51] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah. Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs. *IEEE Transactions on Wireless Communications*, 15(6):3949–3963, 2016.

[52] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah. Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs. *IEEE Transactions on Wireless Communications*, 15(6):3949–3963, 2016. doi: 10.1109/TWC.2016.2531652.

[53] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah. Mobile unmanned aerial vehicles (uavs) for energy-efficient internet of things communications. *IEEE Transactions on Wireless Communications*, 16(11):7574–7589, 2017. doi: 10.1109/TWC.2017.2751045.

[54] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah. Mobile unmanned aerial

vehicles (uavs) for energy-efficient internet of things communications. *IEEE Transactions on Wireless Communications*, 16(11):7574–7589, 2017.

[55] O. Ozdemir, R. Niu, and P. K. Varshney. Channel aware particle filtering for tracking in sensor networks. 2006 Fortieth Asilomar Conference on Signals, Systems and Computers, pages 290–294, 2006. doi: 10.1109/ACSSC.2006.356634.

[56] O. Ozdemir, R. Niu, and P. K. Varshney. Dynamic bit allocation for target tracking in sensor networks with quantized measurements. In *2010 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 2906–2909, 2010. doi: 10.1109/ICASSP.2010.5496156.

[57] F. Palmieri, S. Marano, and P. Willett. Measurement fusion for target tracking under bandwidth constraints. In *2001 IEEE Aerospace Conference Proceedings (Cat. No.01TH8542)*, volume 5, pages 2179–2190 vol.5, 2001. doi: 10.1109/AERO.2001.931175.

[58] G. Papa, P. Braca, S. Horn, S. Marano, V. Matta, and P. Willett. Multisensor adaptive bayesian tracking under time-varying target detection probability. *IEEE Transactions on Aerospace and Electronic Systems*, 52(5):2193–2209, 2016.

[59] M. Rentmeesters, W. Tsai, and K.-J. Lin. A theory of lexicographic multi-criteria optimization. In *Proceedings of ICECCS '96: 2nd IEEE International Conference on Engineering of Complex Computer Systems (held jointly with 6th CSESAW and 4th IEEE RTAW)*, pages 76–79, 1996. doi: 10.1109/ICECCS.1996.558386.

[60] E. A. Riskin. Optimal bit allocation via the generalized bfos algorithm. *IEEE Transactions on information Theory*, 37(2):400–402, 1991.

[61] Y. Ruan and P. Willett. A quantization architecture for track fusion. *ITAES*, 41(2):671–681, 2005.

[62] Y. Ruan, P. Willett, and A. Marrs. Fusion of quantized measurements via particle filtering. In *2003 IEEE Aerospace Conference Proceedings (Cat. No.03TH8652)*, volume 4, pages 4–1967–4–1978, 2003. doi: 10.1109/AERO.2003.1235125.

[63] Y. Ruan, P. Willett, A. Marrs, F. Palmieri, and S. Marano. Practical fusion of quantized measurements via particle filtering. *IEEE Transactions on Aerospace and Electronic Systems*, 44(1):15–29, 2008.

[64] Sarojini Vudumu, Dr. Ratnasingham Tharmarasa, and Dr. Thiagalingam Kirubarajan. Joint bandwidth allocation and assignment of targets to multiple fusion centers for distributed multi-target tracking. *To be submitted to IEEE Transactions on Aerospace and Electronic Systems*, July, 2023.

[65] Sarojini Vudumu, Dr. Ratnasingham Tharmarasa, and Dr. Thiagalingam Kirubarajan. Efficient performance bounded data gathering for distributed multi-target tracking. *To be submitted to IEEE Transactions on Aerospace and Electronic Systems*, July, 2023.

[66] Sarojini Vudumu, Dr. Ratnasingham Tharmarasa, Dr. Thiagalingam Kirubarajan, and Dr. Anne-Claire Boury-Brisset. Efficient quantization for multi-target tracking. *To be submitted to IEEE Transactions on Aerospace and Electronic Systems*, July, 2023.

[67] M. Shamaiah, S. Banerjee, and H. Vikalo. Greedy sensor selection: Leveraging

submodularity. In *49th IEEE conference on decision and control (CDC)*, pages 2572–2577. IEEE, 2010.

[68] M. Stein, A. Kürzl, A. Mezghani, and J. A. Nossek. Asymptotic parameter tracking performance with measurement data of 1-bit resolution. *IEEE Transactions on Signal Processing*, 63(22):6086–6095, 2015.

[69] M. S. Stein, S. Bar, J. A. Nossek, and J. Tabrikian. Performance analysis for channel estimation with 1-bit adc and unknown quantization threshold. *IEEE Transactions on Signal Processing*, 66(10):2557–2571, 2018.

[70] Y. Sun, T. Wang, and S. Wang. Location optimization and user association for unmanned aerial vehicles assisted mobile networks. *IEEE Transactions on Vehicular Technology*, 68(10):10056–10065, 2019. doi: 10.1109/TVT.2019.2933560.

[71] R. Tharmarasa and T. Kirubarajan. Collaborative sensor management for decentralized asynchronous sensor networks. In *Signal and Data Processing of Small Targets 2007*, volume 6699, page 66990Z. International Society for Optics and Photonics, 2007.

[72] R. Tharmarasa, T. Kirubarajan, M. L. Hernandez, and A. Sinha. Pcrlb-based multisensor array management for multitarget tracking. *IEEE Transactions on Aerospace and Electronic Systems*, 43(2):539–555, 2007. doi: 10.1109/TAES.2007.4285352.

[73] R. Tharmarasa, T. Kirubarajan, and T. Lang. Joint path planning and sensor subset selection for multistatic sensor networks. In *2009 IEEE Symposium on*

Computational Intelligence for Security and Defense Applications, pages 1–8. IEEE, 2009.

[74] R. Tharmarasa, T. Kirubarajan, J. Peng, and T. Lang. Optimization-based dynamic sensor management for distributed multitarget tracking. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 39(5):534–546, 2009.

[75] Y. Wang, X. Wen, Z. Hu, Z. Lu, J. Miao, C. Sun, and H. Qi. Multi-uav collaborative data collection for iot devices powered by battery. In *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1–6, 2020. doi: 10.1109/WCNC45663.2020.9120646.

[76] H. Wu, X. Tao, N. Zhang, and X. Shen. Cooperative uav cluster-assisted terrestrial cellular networks for ubiquitous coverage. *IEEE Journal on Selected Areas in Communications*, 36(9):2045–2058, 2018. doi: 10.1109/JSAC.2018.2864418.

[77] Q. Wu, Y. Zeng, and R. Zhang. Joint trajectory and communication design for multi-uav enabled wireless networks. *IEEE Transactions on Wireless Communications*, 17(3):2109–2121, 2018. doi: 10.1109/TWC.2017.2789293.

[78] M. Xie, W. Yi, T. Kirubarajan, and L. Kong. Joint node selection and power allocation strategy for multitarget tracking in decentralized radar networks. *IEEE Transactions on Signal Processing*, 66(3):729–743, 2017.

[79] M. Xie, W. Yi, T. Kirubarajan, and L. Kong. Joint node selection and

power allocation strategy for multitarget tracking in decentralized radar networks. *IEEE Transactions on Signal Processing*, 66(3):729–743, 2018. doi: 10.1109/TSP.2017.2777394.

[80] J. Yan, B. Jiu, H. Liu, B. Chen, and Z. Bao. Prior knowledge-based simultaneous multibeam power allocation algorithm for cognitive multiple targets tracking in clutter. *IEEE Transactions on Signal Processing*, 63(2):512–527, 2014.

[81] Z. Yang, M. Chen, W. Saad, C. S. Hong, and M. Shikh-Bahaei. Energy efficient federated learning over wireless communication networks. *IEEE Transactions on Wireless Communications*, 20(3):1935–1949, 2020.

[82] C. You and R. Zhang. 3d trajectory optimization in rician fading for uav-enabled data harvesting. *IEEE Transactions on Wireless Communications*, 18(6):3192–3207, 2019.

[83] Y. Yuan, W. Yi, R. Hoseinnezhad, and P. K. Varshney. Robust power allocation for resource-aware multi-target tracking with colocated mimo radars. *IEEE Transactions on Signal Processing*, 69:443–458, 2021. doi: 10.1109/TSP.2020.3047519.

[84] Y. Zeng, R. Zhang, and T. J. Lim. Wireless communications with unmanned aerial vehicles: Opportunities and challenges. *IEEE Communications Magazine*, 54(5):36–42, 2016.

[85] Y. Zeng, X. Xu, and R. Zhang. Trajectory design for completion time minimization in uav-enabled multicasting. *IEEE Transactions on Wireless Communications*, 17(4):2233–2246, 2018.

[86] C. Zhan, Y. Zeng, and R. Zhang. Energy-efficient data collection in uav enabled wireless sensor network. *IEEE Wireless Communications Letters*, 7(3):328–331, 2017.

[87] C. Zhan, Y. Zeng, and R. Zhang. Energy-efficient data collection in uav enabled wireless sensor network. *IEEE Wireless Communications Letters*, 7(3):328–331, 2018.

[88] H. Zhang, W. Liu, Z. Zhang, W. Lu, and J. Xie. Joint target assignment and power allocation in multiple distributed mimo radar networks. *IEEE Systems Journal*, 2020.

[89] M. Zhao, Y. Yang, and C. Wang. Mobile data gathering with load balanced clustering and dual data uploading in wireless sensor networks. *IEEE Transactions on Mobile Computing*, 14(4):770–785, 2015. doi: 10.1109/TMC.2014.2338315.

[90] L. Zuo, R. Niu, and P. K. Varshney. Posterior crlb based sensor selection for target tracking in sensor networks. In *2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP '07*, volume 2, pages II–1041–II–1044, 2007. doi: 10.1109/ICASSP.2007.366417.

[91] L. Zuo, R. Niu, and P. K. Varshney. A sensor selection approach for target tracking in sensor networks with quantized measurements. In *2008 IEEE international conference on acoustics, speech and signal processing*, pages 2521–2524. IEEE, 2008.