NEW YORK INSTITUTE OF TECHNOLOGY
College of Engineering
& Computing Sciences

THESIS TITLE:
Passive Detection in Satellite Networks

by

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A Thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Computer Science

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NEW YORK INSTITUTE OF TECHNOLOGY
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2023

Abstract

The utilization of space and the growing issue of debris are anticipated to escalate due to responsive launches and technological advancements, leading to lowered access barriers. The goal of this project is to create a centralized system that integrates diverse satellites, objects, and servers using adaptive algorithmic approaches. The main goal is to develop a prioritized algorithm that can detect, track, and identify intrusive items as well as categorize things in space for the purpose of sensing. The suggested technique takes the field of view and the average distance between satellites and objects and takes measurement correlation into account and avoids duplicate measurements.

Objects are categorized based on the priority scale, enabling us to identify high-priority objects that demand immediate attention. The model employed in this study adopts the flow maximization approach to detect objects while taking their priorities into consideration. We then investigate the scenarios where the objects of high priority and objects of low priority are clustered together. Additionally, we explore the impact of two factors: the object's position within the field of view of the satellites as well as the distance between the objects and the satellites. By prioritizing high-priority objects, the model enhances the overall net flow in the graph, consequently leading to an increased average number of detected objects. Notably, the proposed approach demonstrates that a reduced number of satellites can be adequate when high-priority objects are clustered together.

The evaluation of the proposed algorithm reveals its remarkable capability to detect nearly all objects with an even distribution of the workload among satellites. When high-priority objects are clustered then the average capacity detection of each satellite increases by 90%. When the correlation of measurement is taken into account, the proposed algorithm can yield 50% savings in energy and bandwidth.

Acknowledgements

First and foremost, I would like to thank God Almighty for giving me the strength, knowledge, ability, and opportunity to undertake this project and to persevere and complete it. Therefore, I consider myself very lucky as it was a great chance for learning and professional development.

Bearing in mind the previous I am using this opportunity to express my deepest gratitude and special thanks to my advisor Dr. Anand Santhanakrishnan for continuous support, for his patience, motivation, enthusiasm, and immense knowledge who guided me despite being extraordinarily busy with his duties. I thank my colleague and friend, Ms. Jayasri Tudi for helping develop the simulation experiments.

Besides my advisor, I would like to thank the committee members, Dr. Sertac Artan and Dr. Batu Chalise, for the time they took to review and evaluate my project and provide me with invaluable feedback.

My sincere thanks also go to the Department Chairman, Dr.Yoshikazu Saito, who offered me such a huge opportunity and provided all the support I needed throughout my program.

I perceive this opportunity as a big milestone in my career development. I will strive to use gained skills and knowledge in the best possible way and I will continue to work on their improvement, to attain desired career objectives.

Lastly, I would like to thank my parents for their moral support and my friends with whom I shared my day-to-day experience and received lots of suggestions that improved my quality of work.

Nency Borad

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Chapter 1

Introduction

1.1 Background and Significance

The use of space and debris problems is expected to increase as responsive launches and technological advancements lower access barriers, international players reaffirm national space aspirations, and US policy advances space-related goals. It will become increasingly important to maintain Space Awareness, particularly the monitoring and cataloging of Space Objects. However, the Government will find it challenging to continue providing services in the future due to an increase in the number of new objects and a failure to update tools and procedures [1].

The first methane-fueled rocket in the world to be launched toward orbit was unsuccessful in reaching its target by China's space agency. A rocket from Russia that fell into the Pacific Ocean in January, and a Chinese Long March-5B rocket that crashed onto the earth are just a few of the objects returning to Earth from space that has recently been in the bulletin [2]. Also revolving around the Earth at high speed are huge, small, and microscopic pieces of space junk including everything from tiny meteorites and pieces of satellites that have collided or destroyed.

Even more, high-speed trash particles must be carefully avoided as a result of the frequent collisions between those objects. Spacecraft performed evasive activities to avoid probable collisions with orbiting objects just in 2020. In a space environment where even a coin-sized object can create a lethal hole in a spacecraft, it will be crucial always to know where all space objects of interest are and whether they are moving toward any other things [3].

For many years there has been the old way of fixing telescopes and radars on many distinct known objects at different altitudes, tracking them through the sky, and then repeating the process all time while observing the same objects, with the same equipment. Smart sensing and machine learning for ground-based satellite remote sensing are crucial for space safety and situational awareness [4]. Key applications include space activity facilitation, space traffic management, and collision avoidance.

1.2 Motivation and Proposed Research

In space, the problem of collision between objects is increasing day by day. To reduce the issues with congestion, it was, therefore, necessary to identify the parts of the route with the highest flow. The maximum flow will vary along different pathways. The degree of congestion decreases with increasing maximum flow. The theorem of maximum flow and minimum cut can take the maximum capacity of the route and maximize the flow in a network. But the network works without any priorities so even if there is any harmful object going to collide, the network will consider the path previously taken into consideration without concern about dangerous substances.

The goal of this research is to develop a centralized system using machine learning-based algorithms which contains different types of satellites, objects, and servers. We are developing a prioritized algorithm for detecting, tracking, identifying intruding objects, and classifying objects in space for sensing. Our algorithm will take into account the correlation of measurement if some other satellite is measuring the same object then it will not measure. The algorithm will take into consideration the priorities of the detected object along with capacities and the impact of intruders on the system to get more information about the object. This will help us to keep track of objects, and the path the object will follow, and identify any intruders. We take into account the priority of objects and based on priorities maximum flow is calculated and grouped.

A versatile and effective modeling technique, the max flow problem can be applied to depict a wide range of real-world scenarios. Network optimization and transportation planning are only a few areas where the flow maximization strategy is effective and frequently employed. In a system or network, flow is the movement of a resource or other entity from one place to another. The goal of this technique is to ascertain the greatest flow that may be accomplished in a specific system or network. The adaptability of the flow maximization strategy is one of its main advantages. The ideal placement of items or the routing of cars, for instance, can be determined using the flow maximization approach in transportation planning in order to maximize the flow of goods or traffic as a whole.

The approach aims to investigate the significance of strategic prioritization in maximizing item identification while minimizing resource utilization. The motivation behind this is to enhance the overall efficiency of satellite-based object detection systems. By understanding the impact of priority distribution on detection rates, researchers and practitioners can develop strategies that maximize the detection of critical objects while optimizing resource utilization.

The examination of the suggested method shows that it has a remarkable capacity to detect almost all objects with a balanced workload distribution among satellites. We investigate how two factors influence the results: the object's position in relation to the satellites' field of view and the distance between the objects and the satellites. By giving priority to high-priority objects, the model improves the overall flow in the graph, resulting in a higher average number of detected objects. Comparison of the scenario with assigning random priorities and high priority is with high priority it has a significant impact. It can be observed that by increasing the distance by 2 times, there is a fall in capacity and the average number of objects being detected falls by 90%. We also take into account correlations between objects while performing the experiments to determine the relation by considering the distance. The proposed approach saves energy and bandwidth by 50% when the correlation of measurements is taken into account.

The rest of the thesis is organized as follows. Chapter 2 describes the current art in this research topic and the research gaps. The System model with the maximum flow with and without priority is provided in Chapter **??**. Network and parameters, experimental setup with different scenarios, and numerical results are discussed in Chapter 4 and conclusions are drawn in Chapter 5.

Chapter 2

Literature Review

The literature review is divided into four sections, which include Object Detection in satellites (Section 2.1), Basic optimization approaches (Section 2.2), Flow maximization approach (Section 2.3), and Machine learning approaches (Section 2.4).

2.1 Object detection in satellites

Abercromby et al [5] discovered the range and nature of debris in geosynchronous orbit by getting distributions for the brightness, inclination, right ascension of ascending nodes, and mean velocity for the debris. Fred's [6] experiment tells that there comes the point where the search strategy performs better as the number of Resident Space Objects rises in the geosynchronous orbit belt. Gudzius et al [7] described the U-net architecture which is accurate, quick, and capable of performing a semantic segmentation operation for object recognition in multispectral satellite imagery. AlDahoul et al [8] improved classification performance in major part by concentrating on space object regions and disregarding other unimportant items in the backgrounds.

Agapov et al [9] demonstrated the significance of a more thorough deterministic assessment of the full GEO-protected arc range. Cognion [10] explained the straightforward photometric model to explain the photometric signatures of GEO satellites seen at large phase angles. Michael [11] determined the value by equally weighing the three performance parameters of minimum detectable object size, time lag between 52 further Resident space objects observations, and overall system cost. Fitzgerald [12] established a new standard for object detection performance using a novel passive Wide Field-of-View ground-based optical sensor system idea and data with the deep learning architecture.

Dong et al [13] solved the problem using the progressive enhancement learning model, directed by the visual attention mechanism, and the item can be found and located using time-space information. The accuracy of this method's object detection and its capacity to collect image details have improved, according to experiments. Kang et al [14] discovered the six categories used to group the most significant strategies. Furthermore, in order to support and inspire research on object detection in the context of overhead images, the contrast and analysis was done with publically accessible datasets. Additionally, depending on the various picture sources, the article surveyed the datasets and provided useful details of image resolution and size.

2.2 Basic optimization approaches

Hou and Zhao [15] demonstrated that the two proposed algorithms may effectively minimize the consumption of pathways and more evenly distribute the network's load. Mayouf et al [16] focused on the quality of service requirements by improving the delivery ratio, delivery delay, and communication overhead. Jaesung Park [17] proposed a method in which there is the successful delivery of packets to destinations and better energy consumption. By choosing to delete short exposure data frames that do not significantly increase the overall signal-to-noise ratio of the averaged image, the algorithm presented by Becker [18] enhanced the conventional stack and average approach of creating a long exposure image.

Vasso [1] discussed his Non-Sorted Genetic Algorithm II (NSGA-II) heuristic method to make better Governments Space Domain Awareness Cataloging by optimizing non-traditional sensors. Shi et al [19] invented a new secure routing technique for WSNs that can sustain a higher delivery ratio demonstrating its effectiveness based on global optimization. The modified Dijkstra method has a reduced packet loss ratio since it can more successfully avoid hostile nodes. Compensation for attitude motion allows for accurate object detection even when the altitude is being adjusted. The technique by Zhang [20] performs well for moving space point objects even when the brightness changes.

2.3 Flow maximization approach

Chaudhuri et al [21] proposed a new method by assigning unique values to each vehicle for the security of the system. It does not have any administrative costs or complications. Shailaja et al [22] classified ways of routing called single and metric-based approaches. They used a meta-heuristic algorithm for the calculation of routes by specifying details. Youn et al [23] concluded that the Mobile network faces a critical routing issue by combining location information availability and transmission power control to increase its lifespan. Aggarwal et al [24] designed the protocol to lessen the Denial of Service issue by verifying the authenticity of nodes.

Liu [25] gave a nonlinear formulation, and equilibrium pseudo-flow to solve the multi-commodity flow problem. Whitman et al [26] showed the crucial network linkages by analyzing network vulnerability using a flow-based methodology. Khanal et al [27] introduced the priority-based multi-commodity flow problem in this paper and created a mathematical model for it. Also, give a polynomial time solution. Behrisch and Erdmann [28] demonstrated an algorithm's superior ability to handle missing data by utilizing a real-world highway scenario to demonstrate optimality about maximizing the flows while treating the counts as constraints. Flow-based routing [29] looks to give a degree of service above that of the existing paradigm to handle the growing needs of network applications and traffic, according to the current and ongoing research on it that is currently available.

Almohamad et al [30] increase the total backhaul flow by providing two linear optimization techniques that enhance the association and the formation. The technique allowing for partial demand fulfillment surpasses the binary one in terms of accumulation rate and the proportion, even at low maximum hop and link counts, according to numerical simulations.

2.4 Machine learning approaches

Samiei and Li [31] informed tuning parameters selection should be taken into account to achieve good performance with reinforcement learning object detection models. Bueno at al [32] provided hierarchical image analysis by extracting features from a convolutional neural network for each region proposal. Mathe et al [33] proposed a spatial hypothesis search method in which there are principled sequential models that effectively recognize visual objects by accumulating data from a limited number of image places. Koenig et al [34] employed a reinforcement learning approach using hierarchical tree representation which can be zoomed in by the user.

The state-of-the-art performance of ReinforceNet is shown by extensive experimental findings of Zhou et al [35] on two benchmark datasets, which show that it is capable of improving region selection and learning better agent action representations for reinforcement learning. Samiei and Li [36] put into practice a revolutionary deep reinforcement learning-based active object localization technique by conducting some experiments on the models' performance by examining various hyperparameters and architectural modifications.

Hocking et al [37] introduced an effective unsupervised machine learning method that combines hierarchical clustering, and connected component labeling. The approach uses a patch-based model rather than processing entire images of galaxies. It combines a number of tiny, overlapping patches to represent galaxies.

The current literature has no foundations for the flow maximization of high-priority objects and their impact on detecting the objects with respect to the object's position within the field of view of the satellites as well as the distance between the objects and the satellites. Also, correlation measurement is considered which is developed in this research.

Chapter 3

Proposed Research

3.1 Problem Definition and System Model

3.1.1 Problem Definition

Initially, in space, a different satellite detects various objects. It does not consider the ways in which objects should be detected which is one of the disadvantages of the system if there is any harmful object then the satellite might not detect it and may be dangerous to the Earth. Our goal is to model an adaptive algorithm where all satellites can detect as many objects as possible. So, we developed a system model which detects objects based on angle, distance, and priority. However, we have the following limitations:

1. Processing Power: Satellites have limited processing power onboard. Object detection involves complex computational tasks, especially when dealing with large datasets and multiple objects simultaneously. The available processing power might not be sufficient to handle detection for all objects in the satellite's field of view.

2. Memory and Storage: Satellites have finite memory and storage capabilities. Storing data for all detected objects could quickly deplete the available memory, leading to data loss or corruption. Prioritizing the storage of important or high-priority objects is necessary.

3. Power Consumption: Object detection requires significant power consumption. Satellites must optimize their power usage to ensure long-term mission success. Limiting the number of objects detected can help manage power resources.

4. Bandwidth and Data Transmission: Transmitting data from satellites to ground stations requires sufficient bandwidth. However, bandwidth is often limited and costly. Transmitting data for every detected object in real time might overload the available bandwidth, necessitating a selection of the most relevant or critical objects for transmission.

Although our proposed solution can be made to include all these factors, in order to understand its effectiveness, we abstract all the above factors into a single term called "link capacity". It can be explained by small example below:

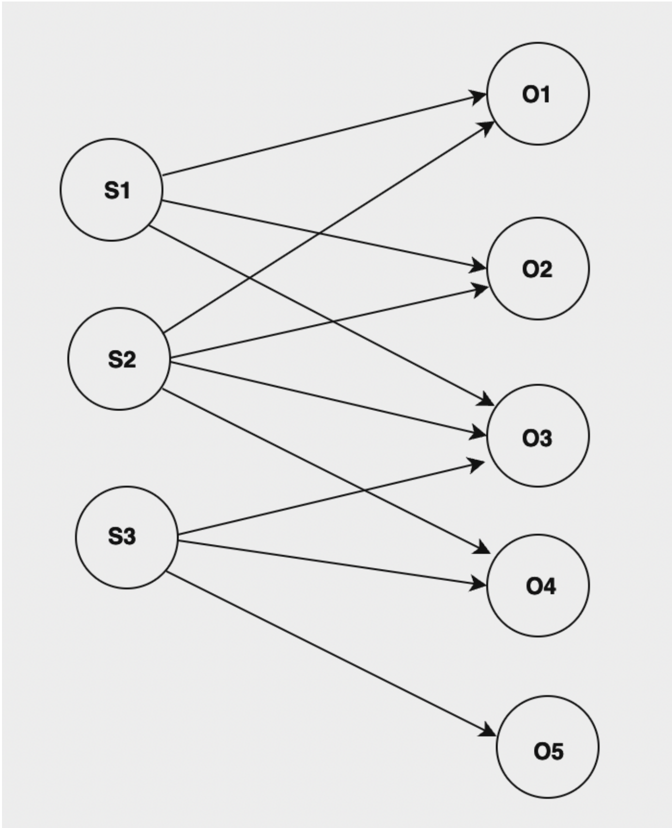

FIGURE 3.1: Satellite detecting objects in field of view

Here, in the network of 3 satellites and 5 objects, each satellite from S_1 to S_3 can detect all objects from O_1 to O_5, but S_1 will detect O_1 to O_3, S_2 will detect O_1 to O_4, S_3 will detect O_3 to O_5 as objects are in the field of view of satellite as shown in Fig. 3.1. However, due to the capacity constraints if S_1 detects O_1, O_2 and O_3 then S_2 cannot detect them. As a result, there may be scenarios where S_1 detects O_1 and O_2 but no other satellite may be able to detect O_1 and O_2.

We normalize the capacities to 1 as shown in Fig. 3.2. The values on the edges from satellites to objects denote the percentage of resources used from the total capacity linked with it. Here, 0.8 denotes that S_1 is using 80% of the resources for O_1, 0.2 means S_1 is using 20% for O_2 and 0 denotes satellite is choosing not to detect an object even though it can because its resources are already used. Since S_1 has exhausted its capacity on O_3 it might not detect O_3. However, if we readjust by S_1 detects O_1 and O_2, S_2 detects O_3 and S_3 detects O_4 and O_5 then all objects can be detected by reducing the load on satellite. So our goal is to model an algorithm that can be adaptive like this to changing environments. So, for this, we use the flow-maximization algorithm which is further explained in section 3.2.

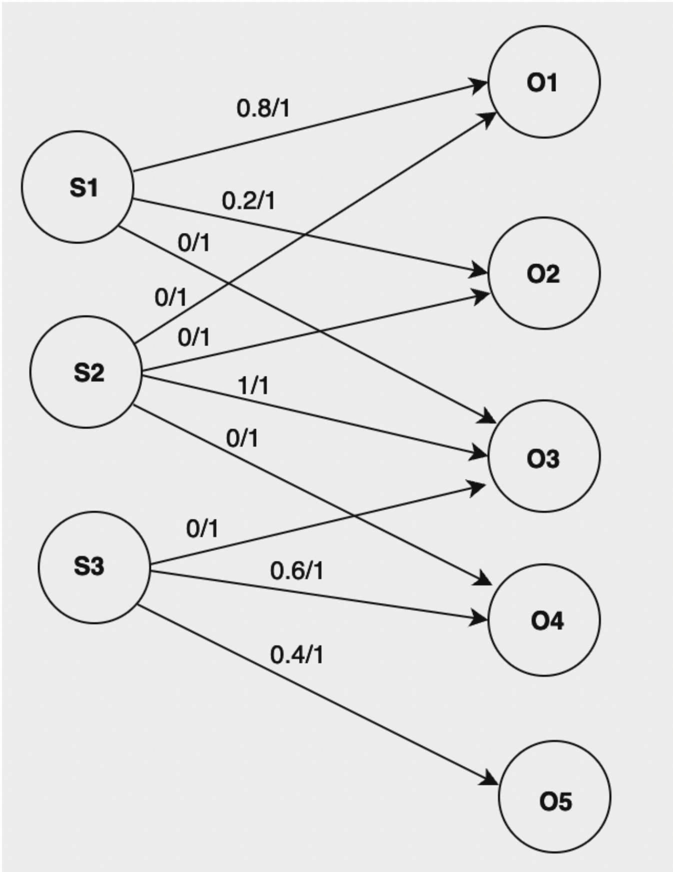

FIGURE 3.2: Satellite detecting objects as per capacity

3.1.2 System Model

The system model of maximum flow is an optimization problem to determine the largest value flow from source S which is starting node to sink t which is the ending point given a flow network G. We consider a network of m satellites trying to detect n objects, where, n > m. Fig. 3.3 shows the satellite designed to detect objects. Consider Graph G(V, E) to be a directed graph with non-negative flow capacities along the edge. The set of all vertices sums the total number of satellites and objects with source and sink node, which is V={S, S_1,S_2,$\cdots$,S_m, O_1,O_2,...O_n,t}. The network consists of directed edges for the objects which are being detected by satellite, where E ⊂{(S, S_i); where 1≤ i≤m , (S_i, O_j) ; where 1≤ i≤m, 1≤j≤n , (O_j, t); where 1≤j≤n} , E is the number of edges. However, note that, $E_{si} = (S, S_i) \in E$, $\forall\ i$, $1 \leq i \leq m$ and $E_{oj} = (O_j, t) \in E$; $\forall\ j$; $1 \leq j \leq n$. Satellites detect objects that are within the field of view and the distance.

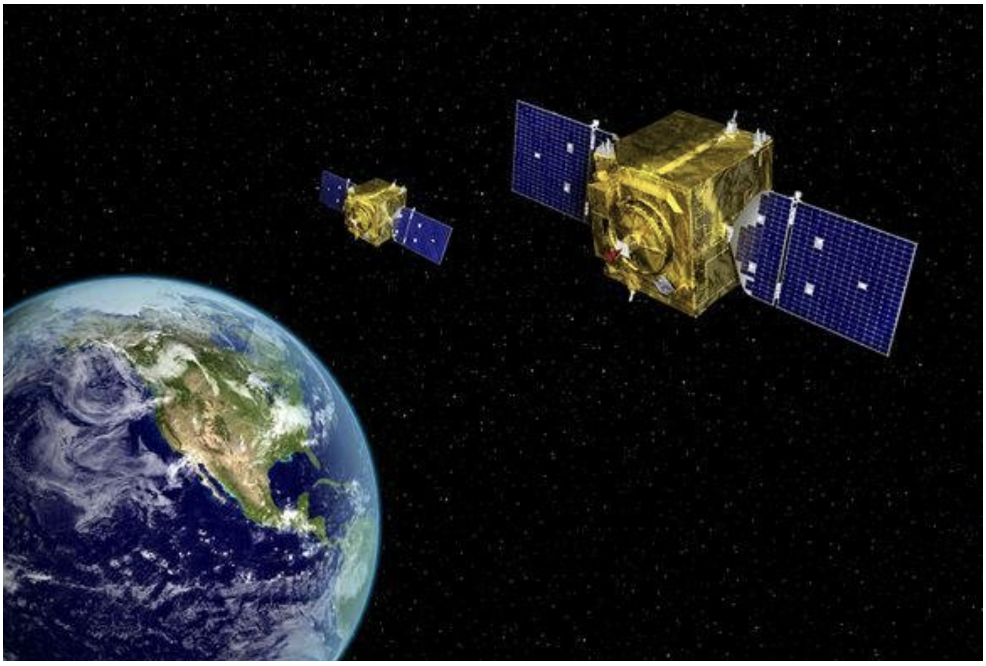

FIGURE 3.3: Model of Satellite designed to detect objects

The field of view of satellite is determined by the maximum angle that can be covered by the satellites viewing camera. For i^{th} satellite it is Φ_i.

The angle between the satellite S_i and the object O_j is calculated by:

$$\theta_{ij} = \arctan\left(\frac{Y_{oj} - Y_{si}}{X_{oj} - X_{si}}\right). \tag{3.1}$$

where, X_{oj} is the x coordinate of the j^{th} object, Xsi is the x coordinate of i^{th} satellite, Yoj is the y coordinate of the j^{th} object, Ysi is the y coordinate of i^{th} satellite.

The probability of a satellite detecting an object depends on two factors: angle and distance. The probability based on angle is calculated by:

$$A_p = \left(1 - \left|\frac{2 * \theta_{ij}}{\Phi_i}\right|\right)^+, \tag{3.2}$$

where, Φ_i is the field of view of i and $(z)^+ = \max(0, z)$, to ensure the probability is between 0 and 1.

Another factor taken into consideration is distance. To calculate the probability based on distance it is necessary to find the distance and distance range between satellite and object.

The distance between satellite S_i and object O_j is calculated as:

$$D_{ij} = \sqrt{(X_{oj} - X_{si})^2 + (Y_{oj} - Y_{si})^2}, \tag{3.3}$$

The distance range D_i of satellite S_i with angle range Φ_i is calculated as [39]:

$$D_i = 200\sqrt{\frac{146}{\Phi_i}} \tag{3.4}$$

The probability based on distance is calculated by:

$$D_p = \left(1 - \left(\frac{D_{ij}}{D_i}\right)\right)^+ \tag{3.5}$$

The probability P_{ij} of satellite S_i detecting object O_j is given by:

$$P_{ij} = A_p * D_p \tag{3.6}$$

It can be further explained by the network of 3 satellites and 5 objects with the source trying to find the maximum flow to sink as shown in Fig. 3.4. Once we obtain the probability P_{ij} of satellite S_i detecting object O_j based on the field of view and distance, we consider obtaining the capacity of edges between satellites and objects by multiplying probability (which will be the value between 0 and 1) with normalized capacity 1. Hence, all the edges between the satellite and the object will have the capacity same as P_{ij}, which will limit the flow on the path from source to sink. The values on the edges from satellites to objects denote the edge's capacity. So, if S_1 is detecting O_2 with 0.3 then there should be another satellite S_2 that needs to detect O_2 to satisfy the capacity. Hence, the information for O_2 should be obtained from two different satellites because of the object getting saturated. Therefore, it is not a reliable way as some objects may get detected with a very low probability when trying to detect all objects. Furthermore, the proposed approach is explained in section 3.2.

3.2 Proposed approach

3.2.1 Flow maximization algorithm

The flow maximization algorithm is used to find the maximum flow in a flow network. A flow network is a directed graph in which each directed edge has an associated capacity (typically, a positive real number). The objective is to maximize the flow from a predefined

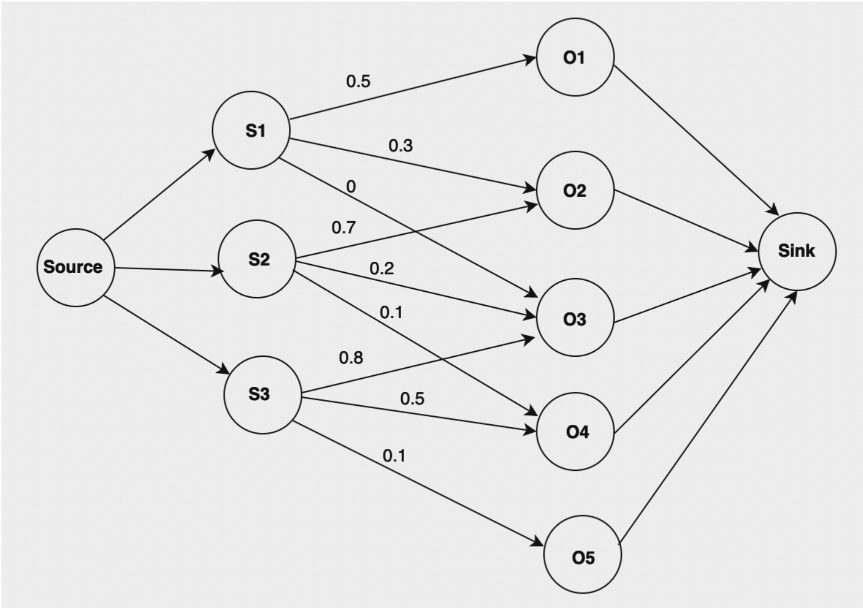

FIGURE 3.4: The network flow diagram with 3 satellites trying to detect 5 objects

"source node" to a designed "sink node". However, two constraints need to be met namely- (i) *the capacity constraint* wherein, the flow on any edge never exceeds the capacity of the edge and (ii) *the flow conservation constraint*, wherein, except for the source and sink nodes, for every other node in the network, the total flow entering a node is equal to the total flow leaving a node.

Here are some basic definitions that are required to understand the flow maximization algorithm:

Residual Graph - The residual Graph shows the potential increase in network flow. Flow equals the edge's capacity minus the edge's flow. So, using our original network, we will update each edge's capacity with the extra flow specific to that edge in order to establish a residual network. The quantity of flow currently passing through the edges of the original network will then be indicated by the addition of reverse edges [40].

Augmenting path - The augmenting path, given a flow network G=(V, E), is a straight line from s to t in the associated residual graph of the flow network [40].

Max flow min cut theorem - The Max-Flow Min-Cut Theorem, a foundational concept in graph theory, establishes a connection between a network's maximum flow and minimum cut. The theorem specifically states that the lowest capacity of a network cut is equal to the maximum throughput through the network. The term "cut" refers to the division of a network's vertices into two distinct sets, with the source vertex being in one set and the sink vertex being in the other. The capacities of the edges that span the cut from the source side to the sink side are added to determine a cut's capacity [41].

3.2.2 Maximum flow without priority

The network without priority in which satellite tries to detect the objects that fall in their range and connect to only those objects which get detected. The capacity of the edges from source node to S_i is taken as some constant, from S_i to O_j is P_{ij} and from O_j to sink is 1. Until the maximum flow is attained, these algorithms work by gradually increasing the flow along a path from the source to the sink. The algorithm determines a source-to-sink path that has capacity available at each step, and then it increases the flow along that path. Up until a point where no more paths with available capacity can be located, the algorithm iterates and increases the flow along accessible paths. The algorithm has now established the network's maximum flow.

A drawback of unassigned priority nodes is that the ensuing flow might not be the most effective or dependable in terms of the overall performance of the network. For instance, routing the flow through certain nodes or edges in a communication network may produce faster and more dependable communication because those nodes or edges may have higher bandwidth or lower latency than other nodes. In this situation, assigning priority to such nodes or edges may be more advantageous than maximizing the flow without taking into account the performance of the network as a whole.

The technique seeks to determine the maximum flow that can be delivered from the source to the sink while satisfying the capacity limitations on the edges in a typical maximum flow situation where nodes are not prioritized. Despite the fact that this strategy often works, there are times when it might not be the best or most desirable choice.

3.2.3 Maximum flow incorporating priority of objects

The network with priority will give priority to the objects and will try to get the maximum flow of object which has high priority. In the case where all objects have equal priorities, we normalize the capacity to 1. While a higher number for the priority indicates that the object has higher importance for detection. Hence, the capacity of the edges from the source node to S_i is considered 10000, from S_i to O_j is P_{ij} times the priority of O_j and from O_j to sink is the priority of O_j. The implementation of the algorithm consists of two functions: Breadth First Search and the Edmonds-Karp algorithm [40]. The Breadth First Search function performs a breadth-first search on the residual graph to find an augmenting path from the source to the sink. The function returns True if there is a path from the source to the sink, and False otherwise. The function also fills a parent array to store the path.

We then implement the Edmonds-Karp algorithm while considering the priorities, which iterates until no more augmenting paths can be found, meaning that the maximum flow has been reached. The flow along each edge represents the amount of flow passing through that edge. The Edmonds-Karp algorithm is based on the concept of finding augmenting paths using BFS, which ensures that the shortest path from the source to the sink is considered at each iteration. This guarantees that the algorithm terminates and finds the maximum flow efficiently [40].

Chapter 4
Results and Discussion

The basic network and its related parameters are provided in Section 4.1 and experimental setup and evaluations are described in Section 4.2.

4.1 Network and parameters

We consider a network of an increasing number of satellites and 50 objects and another network with increasing satellites of 500 objects. A network with 50 objects is having heavy load on the satellite as the average object per satellite is more. While one with 500 objects is considered a light load on the satellite as the average object per satellite gets distributed. A dummy source node is added which connects all satellites and a dummy destination node connects to all objects and the rest of the nodes are the intermediate nodes. Here, 5 satellites are trying to detect 500 objects. The total number of nodes in the network is 505. It is worth noting that as the angle of detection by the satellites increases, the coverage distance decreases, with smaller angles enabling coverage over larger distances.

In order to handle shifting priorities and positions, we are applying machine-learning techniques[38]. The model directly picks up on relative flow volumes, enabling it to deliver accurate flows.

The priority for these objects is assigned on a scale of 1 to 10. High-priority objects are considered to be harmful which means it requires immediate attention. Thus, Near-earth objects, natural disasters, and military activities get a high priority of 10. Weather systems and environmental monitoring get a medium priority of 5. Air traffic and agricultural monitoring get a low priority of 1.

We consider three scenarios based on priorities:

1. Random: Objects with priorities are “randomly” distributed.

2. High: Objects with “high” priorities are clustered together.

3. Low: Objects with “low” priorities are clustered together.

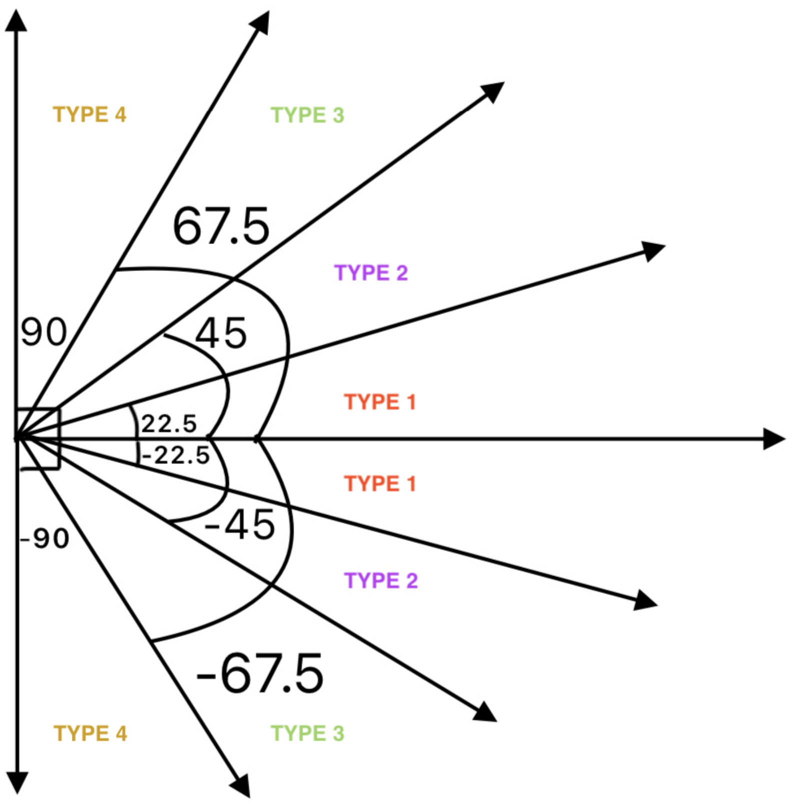

FIGURE 4.1: Categorization of Φ

We consider 4 different types Φ_1, Φ_2, Φ_3, Φ_4 depending on the angles as shown in Fig. 4.1:

Type 1: If satellite has field of view of 45^o then $-22.5^o \leq \Phi_1 \leq 22.5^o$.

Type 2: If satellite has field of view of 90^o then $-45^o \leq \Phi_2 \leq 45^o$.

Type 3: If satellite has field of view of 135^o then $-67.5^o \leq \Phi_3 \leq 67.5^o$.

Type 4: If satellite has field of view of 180^o then $-90^o \leq \Phi_4 \leq 90^o$.

In all the types mentioned above, the negative value detects objects below the horizontal line of the site and the positive value detects the object above the X-axis.

Here, in one of the experiments, satellite 49 detected the object #406, angle calculated θ_{ij} was -3.61 so it comes in the Type 1 - Φ_1 scenario. Angle probability comes to 0.84 with D_i of 1557.29. P_{ij} came upto 0.735.

Figs. (4.2-4.7), shows the various scenarios we considered as categorized in High, and Low priorities. We also consider the average number of objects satellites can detect based on the average distance from satellites.

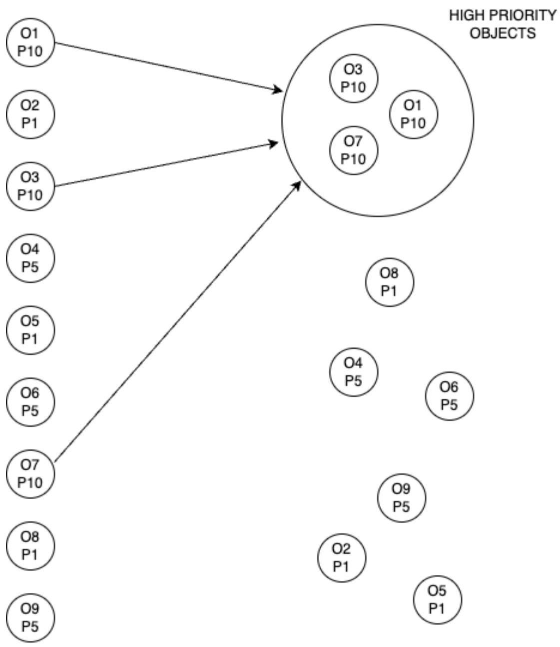

FIGURE 4.2: Objects Categorized based on high priority grouped on top

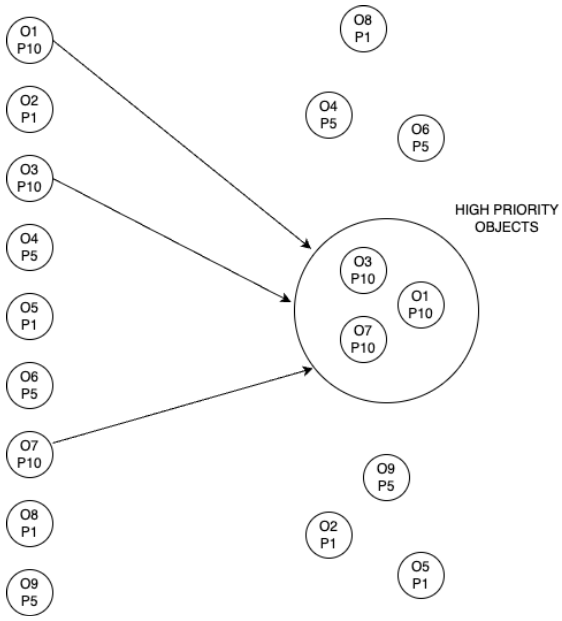

FIGURE 4.3: Objects Categorized based on high priority grouped on middle

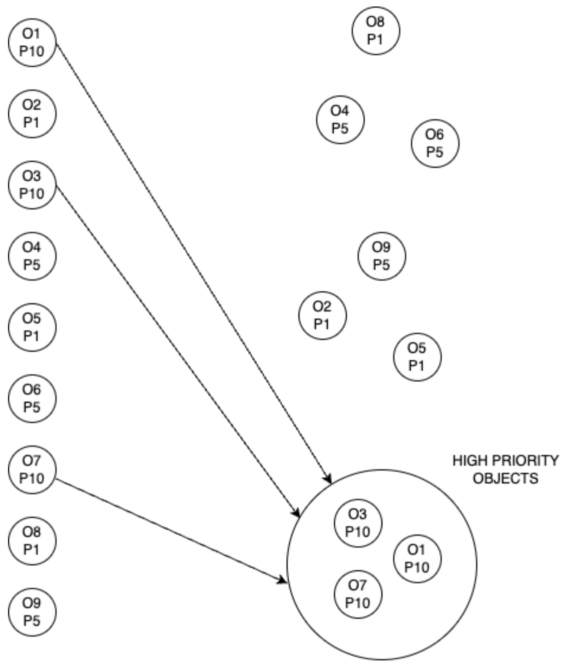

FIGURE 4.4: Objects Categorized based on high priority grouped on down

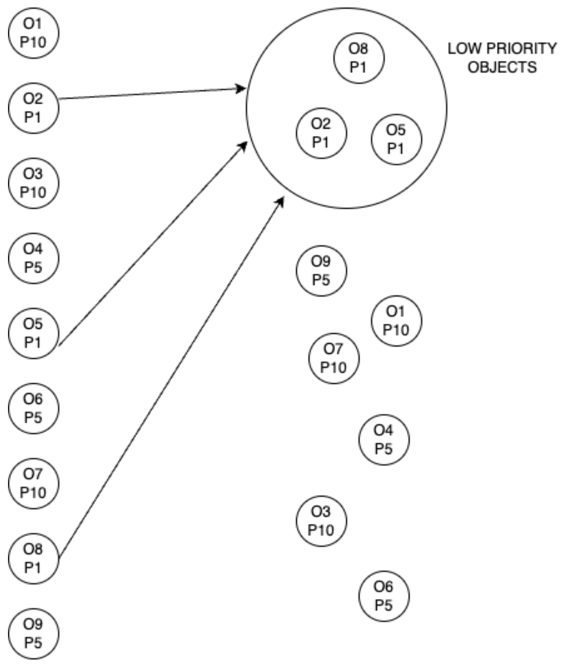

FIGURE 4.5: Objects Categorized based on low priority grouped on top

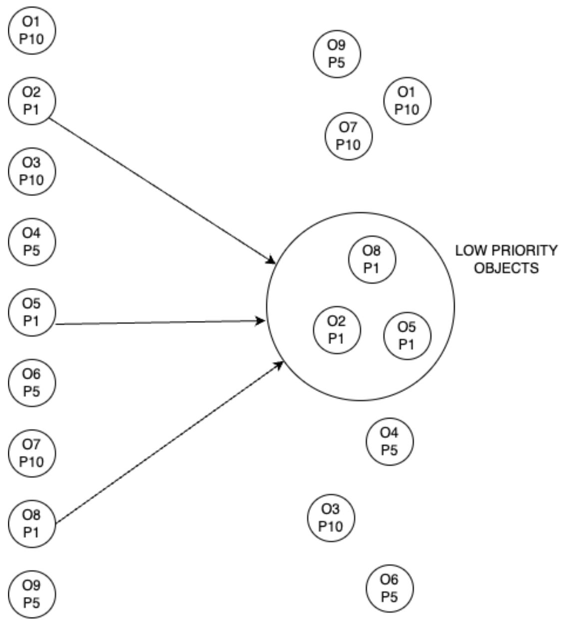

FIGURE 4.6: Objects Categorized based on low priority grouped on middle

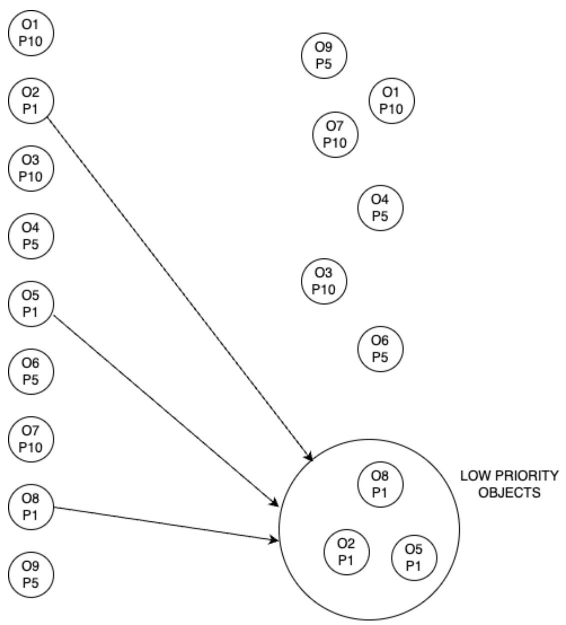

FIGURE 4.7: Objects Categorized based on low priority grouped on down

4.2 Experimental Set Up

We developed a Python-based simulator. We used the Edmonds-Karp algorithm [40] for finding the maximum flow. This algorithm's time complexity is O(VE^2). Where; E is the number of edges and V is the number of vertices [40]. We created a 2-D array to record the capacity of each vertex.

We conducted experiments involving 5 satellites and 50 objects, as well as another set of experiments with 50 satellites and 500 objects. We consider scenario 1 where the objects are taken into consideration with random priorities and another where all high-priority objects are kept together and low priorities objects are clustered with priority levels (ranging from 1 to 10). Additionally, we recorded the execution time of the algorithm. We consider two algorithms for comparison, Edmond-Karp algorithm and Dinic's algorithm [40]. In Edmond-Karp, the maximum value of a network can be obtained from an existing 2-D array using the function maxflow. The advantages of the Edmonds-Karp algorithm include its ease of use, guaranteed termination, robustness in sparse networks, simplicity in analysis, and memory effectiveness. In Dinic's algorithm, termination in a finite number of iterations might struggle due to its layered network approach.

4.2.1 Scenario with objects distributed independent of priorities:

Fig. 4.8 presents a graph of 5 satellites and 50 objects that showcases the relationship between the number of satellites and their ability to detect objects, where priorities are assigned **randomly**. The graph highlights that a higher number of satellites leads to a gradual decline in the overall detection rate. These insights emphasize the need for careful consideration when determining the optimal number of satellites to maximize detection efficiency and effectively prioritize objects in satellite-based object detection systems. When a link or network capacity reaches its maximum, additional satellites may not be able to detect the same object due to the saturation of the network flow.

Fig. 4.9 presents a graph of 50 satellites and 50 objects that showcases the relationship between the number of satellites and their ability to detect objects, where priorities are assigned **randomly**. It can be seen from the graph that till the object gets distributed in 16 different satellites the average number of objects detected was decreasing but if we still keep increasing the number of satellites then it remains constant. It means that the point of 16 satellites is called the threshold point. This suggests that, despite an increase in the number of satellites, there is a limit or saturation point to the number of objects that may be detected successfully. So, one should consider limiting the number of satellites as maximum number of objects can be detected from a lesser number of satellites.

Fig. 4.10 illustrates the graph representing 50 satellites and 500 objects without assigning priorities. The graph shows that initially, a higher number of objects are detected when they are not grouped according to priorities. However, as we increase the number of satellites, there is a decline in the number of detected objects, and at one point it becomes constant. This graph collectively implies that the algorithm will give an even load distribution and because of that the average number of detected objects decreases. The graph makes this relationship easier to understand and offers information on how the detection system is working. To verify, the experiment was made for higher numbers, and the same result is seen.

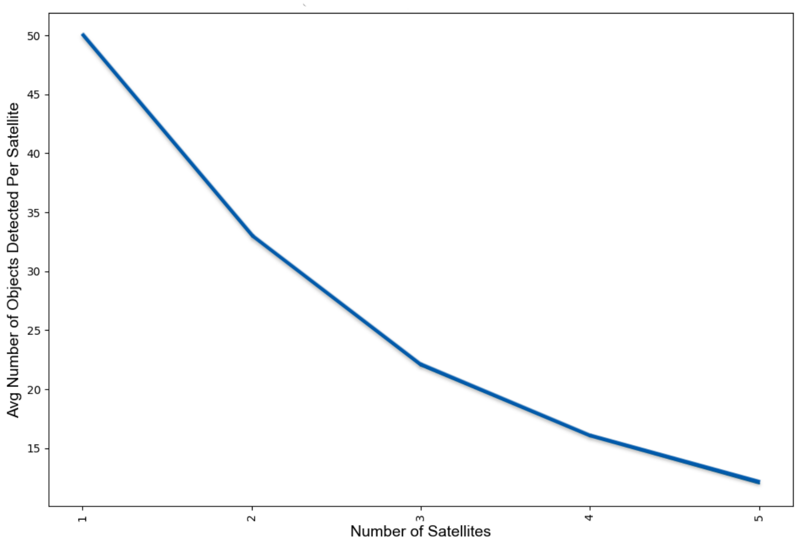

FIGURE 4.8: The graph of **5 satellites** and **50 objects** that showcases the relationship between the number of satellites and their ability to detect objects, where priorities are assigned **randomly**. The graph highlights that a higher number of satellites leads to a gradual decline in the overall detection rate. These insights emphasize the need for careful consideration when determining the optimal number of satellites to maximize detection efficiency and effectively prioritize objects in satellite-based object detection systems. When a link or network capacity reaches its maximum, additional satellites may not be able to detect the same object due to the saturation of the network flow.

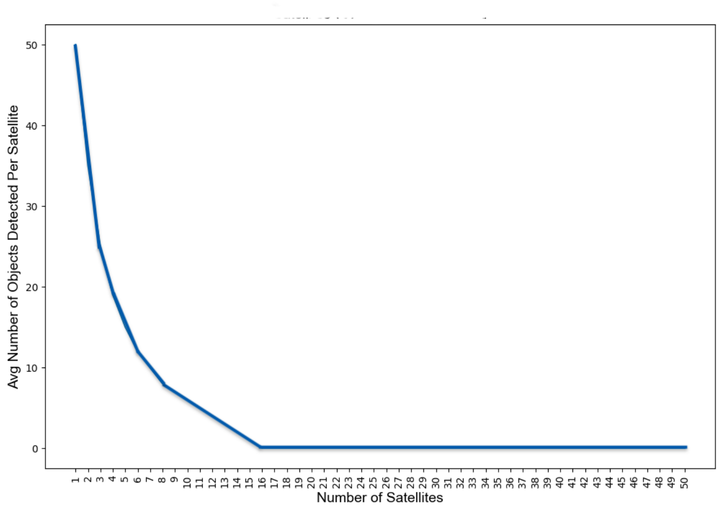

FIGURE 4.9: The graph of **50 satellites** and **50 objects** that showcases the relationship between the number of satellites and their ability to detect objects, where priorities are assigned **randomly**. It can be seen from the graph that till the object gets distributed in 16 different satellites the average number of objects detected was decreasing but if we still keep increasing the number of satellites then it remains constant. It means that the point of 16 satellites is called the threshold point. This suggests that, despite an increase in the number of satellites, there is a limit or saturation point to the number of objects that may be detected successfully. So, one should consider limiting the number of satellites as maximum objects can be detected from lesser number of satellites.

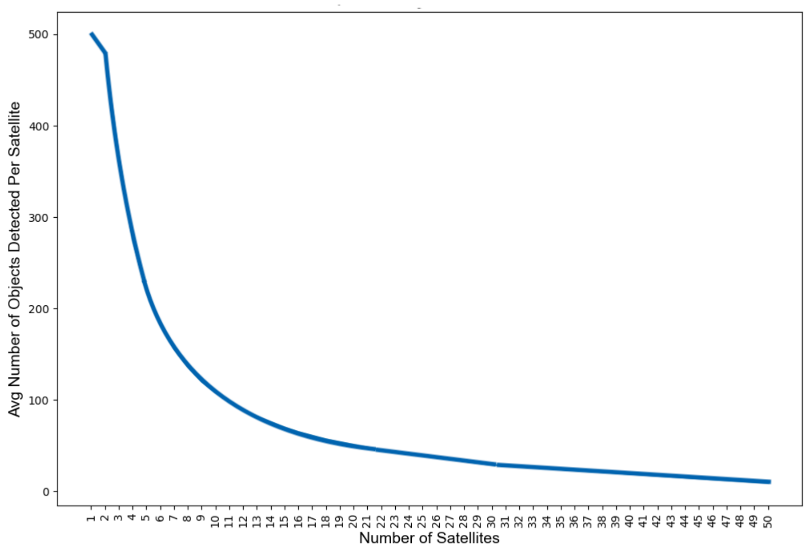

FIGURE 4.10: The graph representing **50 satellites** and **500 objects** without assigning priorities. The graph shows that initially, a higher number of objects are detected when they are **not grouped** according to priorities. However, as we increase the number of satellites, there is a decline in the number of detected objects, and at one point it becomes constant. This graph collectively implies that the algorithm will give an even load distribution and because of that the average number of detected objects decreases. The graph makes this relationship easier to understand and offers information on how the detection system is working. To verify, the experiment was made for higher numbers, and the same result is seen.

4.2.2 Scenario with clustering high priority objects together and low priority objects together:

Fig. 4.11 depicts the graph of 5 satellites and 50 objects with keeping **high-priority** objects together with Fig. 4.8. We are assigning the priorities to the nodes to detect as many objects as possible with a lesser number of satellites being used. According to the plot, satellites aim to find as many objects as they can detect. However, some are saturated other satellites are forced to detect low-priority objects as well. In this way, all objects are detected and at the same time load is evenly distributed between satellites. When high-priority objects are clustered together multiple satellites may detect the same high-priority objects which is good because although there is redundancy it ensures high-priority objects are detected. So the capacity is increased. This method emphasizes how crucial strategic prioritizing is for maximizing item identification while utilizing the fewest resources possible. It advances knowledge of satellite-based object detection techniques and provides information for developing efficient algorithms and systems in a variety of industries, including surveillance, monitoring, and disaster management.

Fig. 4.12 depicts the graph of 50 satellites and 500 objects with keeping **high-priority** objects together. provides valuable insights into object detection capacity by comparing it with Fig. 4.10. The results demonstrate that the node with the highest object detection capacity is associated with the fewest satellites when priorities are assigned. However, as the number of satellites increases, the detection capacity remains constant until the point at which high-priority objects are grouped. Once priorities are distributed, the average number of detected objects decreases. These findings highlight the significance of strategic satellite deployment and prioritization to optimize object detection efficiency.

Fig. 4.13 depicts the graph of 50 satellites and 50 objects with keeping **high-priority** objects together where the total number of objects and satellites are equal. In this case, also it saturates.

Fig. 4.14 shows the plot of **50 satellites** and **500 objects** with keeping **low-priority** objects together similar decline in the detection of objects can be seen.

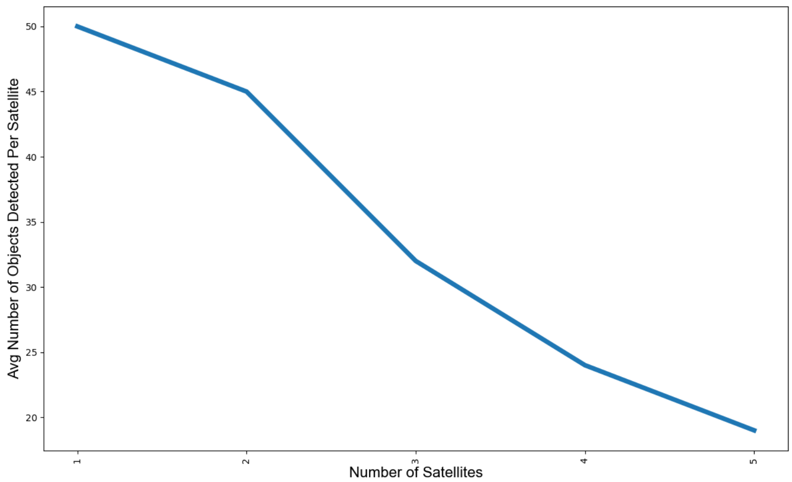

FIGURE 4.11: Comparing this graph of **5 satellites** and **50 objects** with keeping **high-priority** objects together with Fig. 4.8. We are assigning the priorities to the nodes to detect as many objects as possible with a lesser number of satellites being used. According to the plot, satellites aim to find as many objects as they can detect. However, some are saturated other satellites are forced to detect low-priority objects as well. In this way, all objects are detected and at the same time load is evenly distributed between satellites. When high-priority objects are clustered together multiple satellites may detect the same high-priority objects which is good because although there is redundancy it ensures high-priority objects are detected. So the capacity is increased. This method emphasizes how crucial strategic prioritizing is for maximizing item identification while utilizing the fewest resources possible. It advances knowledge of satellite-based object detection techniques and provides information for developing efficient algorithms and systems in a variety of industries, including surveillance, monitoring, and disaster management.

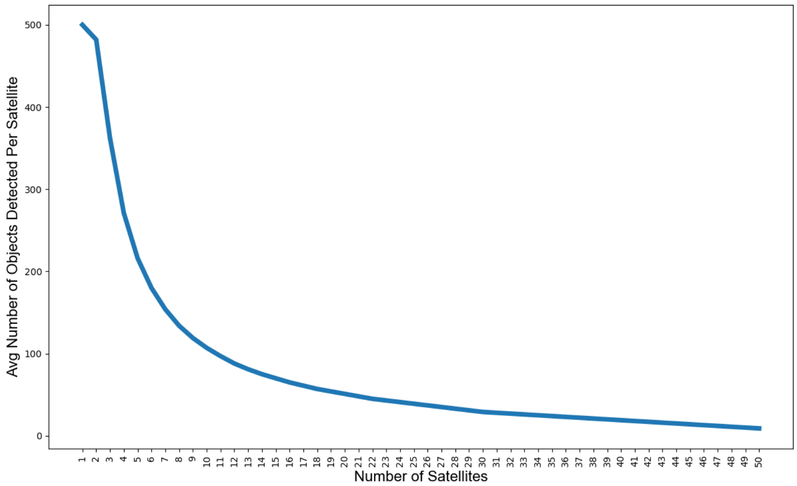

FIGURE 4.12: The analysis of the graph depicting **50 satellites** and **500 objects**, with **high-priority** objects kept together, provides valuable insights into object detection capacity by comparing it with Fig. 4.10. The results demonstrate that the node with the highest object detection capacity is associated with the fewest satellites when priorities are assigned. However, as the number of satellites increases, the detection capacity remains constant until the point at which high-priority objects are grouped. Once priorities are distributed, the average number of detected objects decreases. These findings highlight the significance of strategic satellite deployment and prioritization to optimize object detection efficiency.

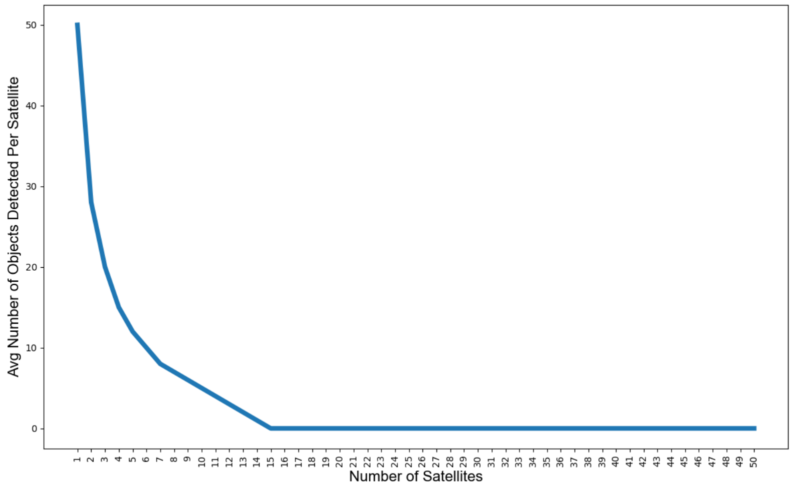

FIGURE 4.13: Comparing Figure 4.9 with the graph of **50 satellites** and **50 objects** with keeping **high-priority** objects together where the total number of objects and satellites are equal. In this case, also it saturates.

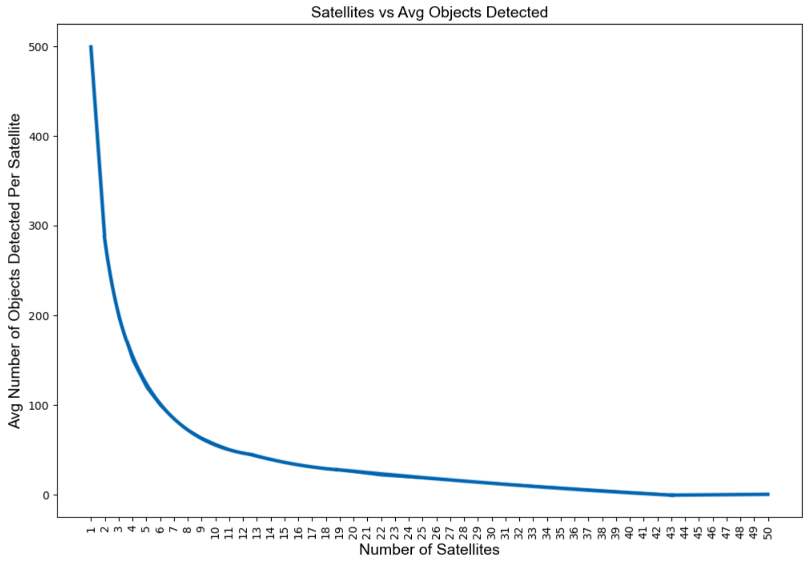

FIGURE 4.14: The plot is of **50 satellites** and **500 objects** with keeping **low-priority** objects together similar decline in the detection of objects can be seen.

4.2.3 Considering Average distance with response to detection of objects:

Figs. (4.15-4.17) shows a scenario of detecting an average number of objects per satellite while keeping in mind the average distance from satellites. Figs. (4.15-4.17) shows average objects detected when ranging **average distance** from 100 to 300. Our algorithmic approach gives a quantitative handle on how this reduction takes place. It can be seen that the capacity decreases and the average number of items being identified drops by 90% when the distance is doubled. The ability to track and detect objects in close proximity is likely due to the enhanced resolution and precision of the satellite's sensors in capturing data at shorter distances. The reduced proximity between the satellite and objects makes it more challenging for the satellite to maintain an exact track of these objects, resulting in decreased detection rates.

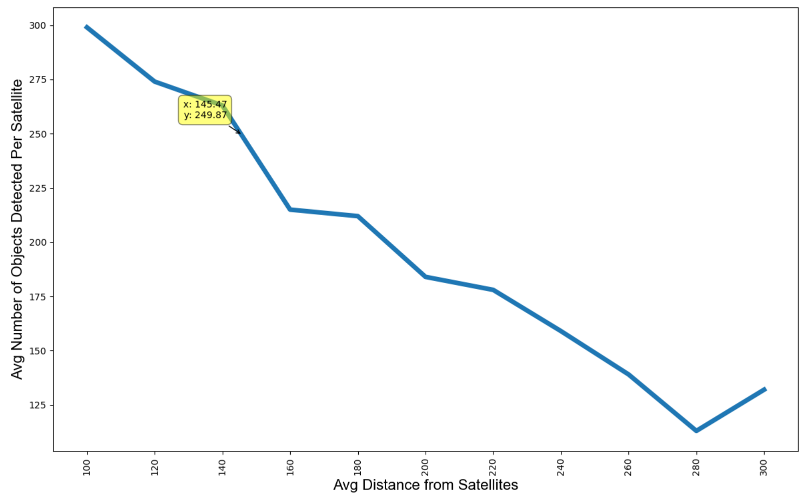

FIGURE 4.15: The graph shows average objects detected when ranging **average distance** from 100 to 300. The graph indicates that the proximity of objects to the satellite significantly impacts the chances of detection. The ability to track and detect objects in close proximity is likely due to the enhanced resolution and precision of the satellite's sensors in capturing data at shorter distances. The reduced proximity between the satellite and objects makes it more challenging for the satellite to maintain an exact track of these objects, resulting in decreased detection rates.

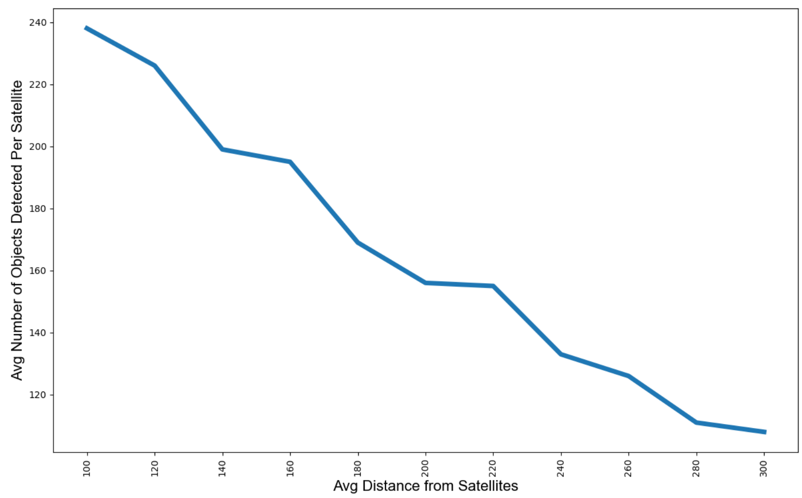

FIGURE 4.16: The graph shows average objects detected as per the satellite and similar results are observed.

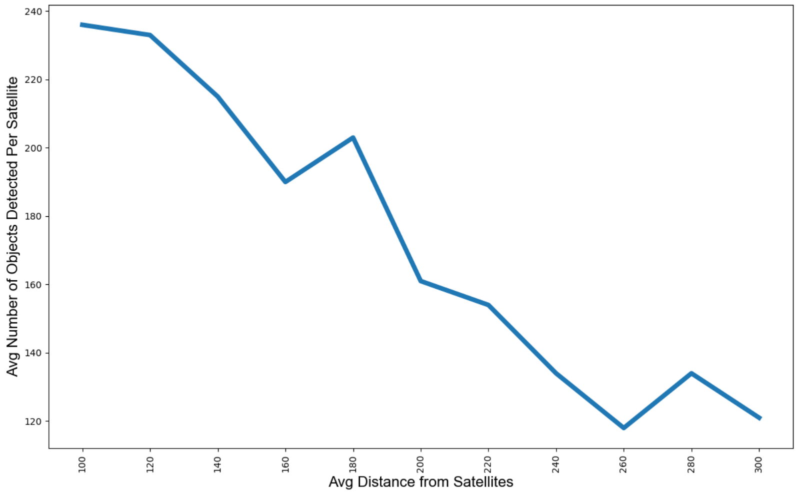

FIGURE 4.17: The graph shows average objects detected based on the satellite and the curve is the same as reported in previous experiments.

4.2.4 Considering Angle of detection of objects:

Fig. 4.18 shows a scenario of detecting an average number of objects per satellite while keeping in mind the angles from satellites. We considered the average angle of 80 with respect to the satellite. The graph shows average objects detected based on **angle** between 20 to 80. The graph reveals that the detection capability of the satellite is closely linked to the chosen observation angle range. The satellite's ability to capture fine details and analyze objects within a narrower range enhances its detection performance. This can be particularly valuable in scenarios where a specific region or area of interest is known, allowing the satellite to concentrate its resources on that targeted range.

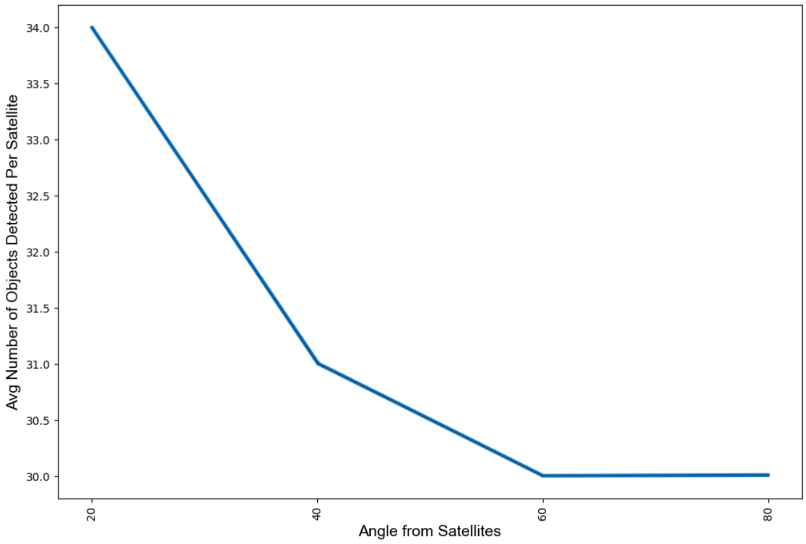

FIGURE 4.18: The graph shows average objects detected based on **angle** between 20 to 80 . The graph reveals that the detection capability of the satellite is closely linked to the chosen observation angle range.The satellite's ability to capture fine details and analyze objects within a narrower range enhances its detection performance. This can be particularly valuable in scenarios where a specific region or area of interest is known, allowing the satellite to concentrate its resources on that targeted range.

4.2.5 Considering correlation measurements:

One feature that can be exploited in order to reduce the bandwidth and energy load on satellites is the linear or non-linear dependants of objects on each other. A popular statistical measure for determining the linear dependants between two objects is the Pearson **correlation between the objects**, which is a number between -1 and 1, with 0 denoting no linear correlation, and ± 1 denoting a perfect linear correlation. We used the magnitude of the Pearson correlation coefficient to measure the linear correlation between objects [42].

Let the priority of object O_j be R_j and that of object O_k be R_k; $R_k > R_j$. We now modify the priority of object O_j as $\tilde{R}_j = R_j(1 - \rho_{jk})$, where $\rho_{jk} \in [0, 1]$ is the magnitude of Pearson correlation coefficient between objects O_j and O_k. In general, for object O_j being correlated with multiple objects.

$$\tilde{R}_j = R_j \prod_{\substack{k \\ R_k > R_j}} (1 - \rho_{jk}) \tag{4.1}$$

We update the priorities of the graph of the objects and implement the max flow algorithm. Fig. 4.19 and Fig. 4.20 show the average number of objects detected with and without exploiting correlation. As observed the average number of objects detected per satellite reduced from 200 to 100 for about 16 satellites. However, with fewer measurements, all the information is obtained because of the correlation. In terms of saving bandwidth and energy, this could lead to about 50% savings because of the fewer measurements made without compromising on the amount of information transmitted.

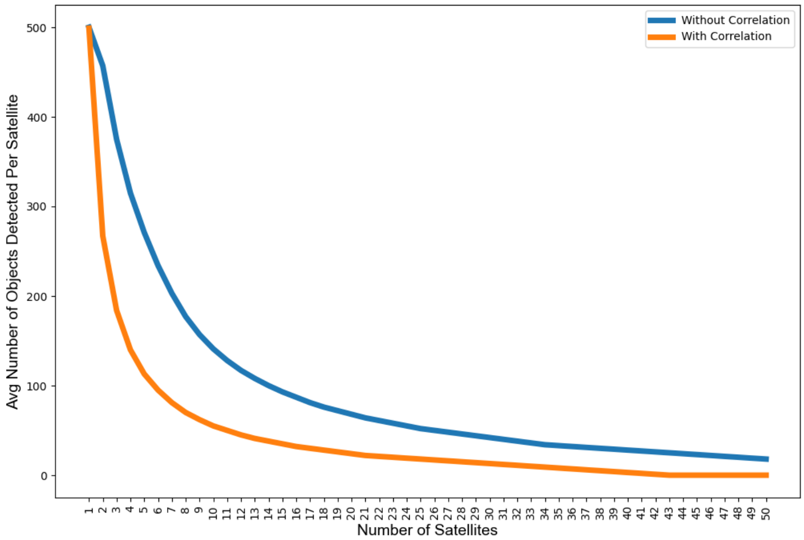

FIGURE 4.19: The graph shows the comparison of objects with and without correlation when priorities are randomly assigned.

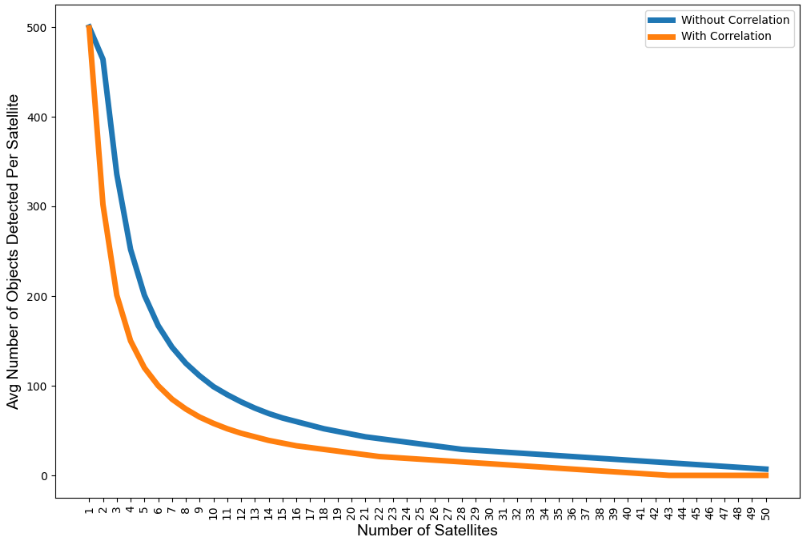

FIGURE 4.20: The graph shows the comparison of objects with and without correlation when high-priority objects are clustered.

Chapter 5
Conclusion

This project developed a centralized system that seamlessly integrates multiple satellites, objects, and servers through the application of machine learning techniques. When numerous satellites are monitoring the same object, the technique minimizes redundancy by minimizing duplicate measurements by considering these parameters. Our study highlights the significance of classifying things according to their priority scales, enabling the identification of high-priority objects that necessitate prompt attention. We further investigated scenarios where high-priority and low-priority objects are clustered together, examining the impact of object position within the satellite's field of view and the distance between objects and satellites.

Our model uses the flow maximization method while taking item priority into account to maximize detection effectiveness. High-priority objects are given priority by the model, which also enhances the graph's overall net flow and raises the average number of detected objects. Remarkably, our results show that the proposed method still works when high-priority items are grouped together, even with fewer satellites.

The evaluation of the proposed algorithm has demonstrated its impressive capability to detect almost all objects while ensuring an equitable distribution of the workload among satellites. By clustering high-priority objects, the average capacity for detection on each satellite increases substantially, achieving a remarkable 90% improvement. Furthermore, the consideration of correlation in the measurement process has proven to be highly beneficial. The proposed algorithm leverages this correlation to yield a substantial 50% savings in energy and bandwidth. This signifies a significant advancement in the field of object detection in satellite systems. The knowledge obtained from this research can be used in a variety of fields, including surveillance, environmental monitoring, and disaster management.

The development of analytical models and tools to prove the numerical results is the topic for future investigation.

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