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Meta-heuristic Black Widow Optimization Algorithm for Solving M Connected Coverage in Internet of Things

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Abstract: Merely addressing the coverage issue in isolation is insufficient within the context of IoT, since the transmission of data to the base station is also a critical factor to consider. This necessitates the search for an energy-efficient approach to address the issue of linked coverage. This research study focuses on the topic of m- connected target coverage in IoT. In this problem, each sensor node is needed to have at least m additional sensor nodes within its communication range. The amount of necessary connection and coverage might vary, ranging from high to low based on specific requirements. In this study, we provide a heuristic approach to address the issue of m-connected target coverage. The proposed method involves determining an initial cover and then verifying its m- connectivity. This work primarily focuses on the concept of m- connectivity in relation to simple coverage. In this study, we use a model influenced by the meta heuristic algorithm namely Black Widow Optimization algorithm. In this model, a cluster is defined as a group of sensor nodes that meet the criteria of m- connectivity and the desired amount of coverage. Sufficiency is achieved when at least one of these nodes communicates the monitored information to the base station. The simulation results demonstrate that the suggested strategy outperforms existing state-of-the-art algorithms.

Keywords: *Internet of Things, black widow optimization algorithm, m connected target coverage, meta heuristic algorithm*

1. Introduction

The IoT has seen significant growth, resulting in increased convenience for individuals [1–3]. The advent of fifth-generation mobile telecommunications technology (5G) is expected to facilitate the development of Internet of Things (IoT) technologies [18]. The Wireless Sensor Network (WSN) may be regarded as an integral component of the IoT [19]. It is a network that consists of several sensor nodes with limited resources [20]. The Wireless Sensor Network (WSN) has extensive use in several domains such as healthcare, military operations, and weather monitoring [21]. To get comprehensive monitoring coverage within a designated region, it is customary to install a substantial quantity of nodes. However, this approach incurs significant expenses and might result in communication conflicts. The optimization of mobile node deployment and the achievement of a wider coverage area with a reduced number of nodes have emerged as prominent areas of focus in the field of wireless sensor network research [22].

Currently, the primary emphasis of research on the WSN coverage issue is centered on the optimization of dynamic network coverage using the binary coverage model. As a result, two distinct kinds of dynamic network coverage approaches have been developed [23]. One such approach for optimizing coverage is via the use of geometric shapes. Sung and Yang [24] proposed a network coverage optimization technique based on Voronoi diagrams. However, this approach is associated with intricate theoretical and computational challenges. The second approach utilizes clever algorithms, such as particle swarm optimization (PSO) [25,28], whale optimization algorithm (WOA) [26], and firefly algorithm (FA) [27], that circumvent the need for intricate theoretical derivation. However, this particular approach is susceptible to the issue of being held captive by untimely convergence and local optimism.

The determination of the coverage requirement is contingent upon the specific application at hand. Certain applications need uninterrupted service at all times, but for other purposes, there is a small flexibility in the coverage requirement [4]. The temporal window within which the sensors are capable of sensing or communicating is constrained due to the finite nature of the batteries. The examination of connection in IoT's, together with considerations about coverage, is of utmost importance [5]. The connection between two sensor nodes is established when they are situated within the communication range of one another. The establishment of connectivity is contingent upon the stochastic arrangement of nodes [6]. The concept of $m-$connectivity asserts that within a sensor cover, which is a subset of sensor nodes that satisfies a certain degree of coverage, each node is linked to a minimum of m additional sensor nodes inside the same cover. The deployment of sensors may be classified into

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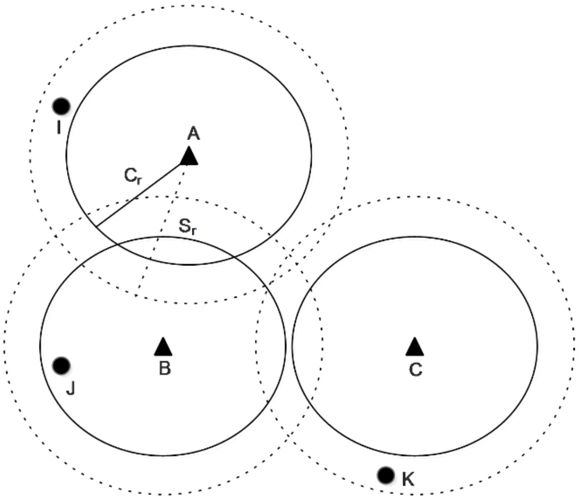
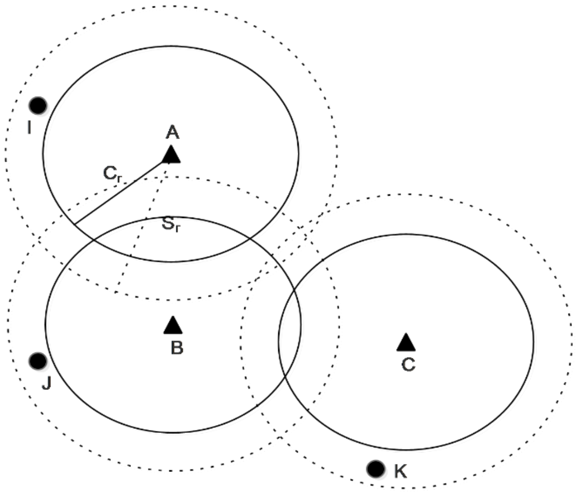
two main categories: deterministic and random. The optimization of sensor node placement in deterministic deployment may lead to the maximization of coverage. Random deployments are favored in situations when the specific information about the location is not known in advance. When sensor nodes are deployed in a random manner, it is possible that some items inside the zone may have a high density of coverage, while others will have a low density of coverage.



(a) Non-Connected Diagram



(b) Connected Diagram

Fig. 1. Linked and Non-Connected Graphs

To enable effective information exchange, Figure 1(a) shows that the sensor nodes A and B have links, but sensor node C is not connected to any of them. Although all the targets T=$\{I, J, K\}$ are included by the set of sensor nodes S=$\{A, B, C\}$, it should be noted that the sensor node C is not interconnected with any of the other sensor nodes. Consequently, this graph may be classified as a non-connected graph. Figure 1(b) depicts a scenario where the sensor nodes, denoted as S, are interconnected with at least one additional sensor node and collectively provide coverage for the whole target area, denoted as T. This configuration may be referred to as a connected graph. This research aims to investigate the problem of minimizing the number of sensor nodes required for a linked network.

Because the number of possible solutions grows exponentially with problem size, the computational complexity of the problem also grows as the problem gets bigger. That's why this issue has been dubbed NP-Hard. On the other hand for solving NP-hard problems, meta-heuristic optimization algorithms are in prime fact due to its positive evolving nature to solve optimization problems. In this research work, Black Widow Optimization algorithm is used to solve the potential location identification to deploy the sensor nodes to keep all sensor nodes connected together.

The subsequent sections of the article have been structured in the following manner: Section 2 pertains to the literature review conducted in the context of the research in this specific IoT and WSN domain. Section 3 presents a comprehensive analysis of the problem addressed in this paper. Section 4 focuses on the utilization of Discrete Black Widow optimization algorithm as a solution approach for resolving the coverage issue with m connections. Section 5 includes the test findings and subsequent discussions. Section 6 concludes with the paper's closing thoughts.

2. Related Work

In their study, the authors [7] introduced a novel metaheuristic method that utilizes ant-lion optimization (ALO) to address the challenges associated with sensor coverage and sensor sensing perception performance. The approach described in this study converts the task of achieving reliable deployment of wireless sensors into a maximization problem, thereby demonstrating the effectiveness and efficiency of this algorithm in optimizing sensor coverage. The method's deployment approach is superior to the sensor coverage attained by the genetic algorithm (GA_WSN) and particle swarm optimization (PSO_WSN), which are frequently employed for sensor deployment applications, according to the results obtained by the method's algorithm. Please provide a reference for the information you mentioned. In order to mitigate the issue of insufficient sensor coverage, a novel approach using the grey wolf optimizer (GWO) was introduced by [8] for sensor random deployment.

In order to solve the sensor deployment coverage problem, Liao et al. [9] built two complete coverage models, central installation and overlay installation, using the firefly swarm algorithm (FA). The coverage effectiveness and mobility problems related to these two models were then compared by the researchers [10]. The studies discussed in this context are founded upon the first random deployment of sensors. Prior to addressing the secondary deployment of sensors, it is important to note that the randomly produced nodes in the original deployment are in close proximity to the actual scene. This proximity is advantageous for the successful implementation of the application. The study presented in reference [11] not only focuses on the generation of scientifically random deployment nodes for sensor nodes, but also introduces a technique for generating data packets. This approach demonstrates significant utility in simulating the performance of IoT\s.

It is important to note in the context of algorithmic efficiency that even though the intelligent optimization algorithm exhibits robust optimization capabilities, a limited number of design parameters, and efficient execution speed, it is not without its drawbacks. In contrast to other conventional algorithms, the SSA method, as described by Xue and Shen [12], has distinct benefits in terms of parameter design and solution accuracy. Nevertheless, the issue of inadequate population variety and the susceptibility of particular populations to local optimization remains a concern. The issue of sensor network coverage is inherently complex and encompasses several dimensions. This study introduces the establishment of the goal function of coverage inside a high-dimensional mathematical model. Hence, it is essential to address the issue of inadequate population variety, as it might lead to a tendency towards local optimization.

To solve the problem at hand, this research study uses the firefly algorithm and the elite reverse method. Furthermore, a brand-new strategy known as the enhanced sparrow search algorithm based on firefly (EFSSA) is presented. The study by [13] investigated population diversity's capacity for optimization in the elite reversal method within the particle swarm optimization algorithm. Sengathir et al. [14] used the artificial bee colony algorithm with the firefly technique in their study to improve the durability of wireless sensor network clustering difficulties. Additionally, a number of academics have extended the operational lifetime of wireless sensor networks by combining the SSA method with the BSA technique [15] [16]. Three distinct enhanced solutions for the robot route planning issue were presented in [17] within the context of SSA. This study integrates the elite reverse strategy and firefly algorithm in order to enhance the efficacy of the intelligent optimization algorithm in addressing the issue of sensor coverage, as shown by the sparrow search.

3. Problem Definition

Let us suppose a scenario in which there exists a set of x sensor nodes, denoted as $\{A_1, A_2, \dots, A_x\}$, inside the area G. Additionally, there are y targets accessible, represented by the set $T = \{K_1, K_2, \dots, K_y\}$. In the specified area G, every sensor node has a communication range denoted as C_r, which enables it to establish contact with other sensor nodes within the field. Additionally, each sensor node has a sensing range denoted as S_r, allowing it to detect the presence of a specific target denoted as K_i, where i belongs to the set T. If the distance between sensor nodes A_i and A_j is less than the threshold S_r, it may be inferred that the nodes A_i and A_j are interconnected, where $i\ and\ j$ are elements of the set x. The coverage matrix, denoted as MCN, is a mathematical construct that may be precisely characterized as

$$MC_i = \{1 \qquad if\ K_i \le S_r(A_j) \qquad i \in y, j \in x\ 0 \qquad otherwise \tag{1}$$

And the construction matrix can be defined as

$$MCN_i = \{1 \qquad if\ D(A_i, A_j) \le C_r \qquad i, j \in x\ 0 \qquad otherwise \tag{2}$$

4. Proposed System

The mating behavior of black widow spiders is characterized by distinctiveness, notably including a specialized phase often referred to as cannibalism. During this phase, spiders who possess inadequate fitness are disregarded within the population, leading to a fast convergence and effectively mitigating the occurrence of local optima. It has been shown that the optimal global solution may be achieved by the Bacterial Foraging Optimization (BWO) algorithm via the careful management of the trade-off between exploration and exploitation. Therefore, the BWO algorithm has been selected for this study as a potential solution for finding potential positions for placing sensor nodes. The following subsections will examine the various steps of the BWO algorithm.

Next generation solution:

A new cohort emerges via the mating of distinct sets. Each couple engages in distinct mating behavior simultaneously, apart from the rest of their network. Upon each reproductive event, the female spiders deposit around 1,000 eggs; however, only a limited number of the more resilient spider progeny successfully survive. To replicate the random numbers inside the matrix of the widow, it is necessary to generate an Alpha matrix within the algorithm. In the following equation, the variables I_1 and I represent parents and offspring, respectively, and are used in their construction.

$$\{P_1 = a \times I_1 + (1 - a) \times I_2\ P_2 = a \times I_2 + (1 - a) \times I_1 \tag{8}$$

There is no need to replicate arbitrarily chosen integers since this process is iterated $\frac{N}{2}$ times. In the final analysis, children and mothers are included into the group and evaluated based on their levels of physical fitness. A select group of individuals with high cannibal ratings have been granted admission to the recently established population. These norms have an impact on all partnerships.

Cannibalism:

This section depicts three separate categories of male predators. To begin, it is worth noting the phenomenon of the black widow spider engaging in cannibalism by consuming her mate either during or after sexual intercourse. The algorithms used in this study facilitated the differentiation of individuals depending on their fitness levels, specifically with regards to gender. In the realm of arachnids, some robust spiders engage in the act of consuming their feeble comrades, therefore exhibiting a kind of cannibalism known as intraspecific predation. The Cannibalism Score (CR) is a metric used to quantify the number of survivors in the context of these algorithms. Occasionally, a distinct kind of ogre has been documented, exhibiting a peculiar behavior of consuming its own mother in the guise of little arachnids. Fitness values are used as a means of differentiating between spiders with low and high levels of strength.

Mutation:

At now, a selection of Mute Pop members is being made by the populace in a random manner. There are two essential elements inside the array seen in Figure 2 that may be altered for each solution. The silent population is built based on mutation rates.

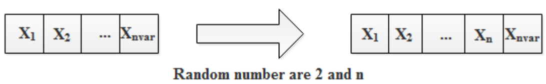


Fig. 2. Mutation in BWO

Mapping BWO – m Connected Coverage IoT

In the context of BWO, each variable is regarded as a prospective deployment zone for a sensor node A_i, where A_i is an element of the set {0,1}. The practice for solving m Linked Coverage using the BWO technique is shown in Algorithm 1.

Algorithm 1: BWO for m −connected coverage problem
Input: Number of sensor nodes y, Number of Targets x, objective function $f()$, Popuation size (N), D – number of potential positions

Begin
 	
for each $i \in N$ ***do***
for each j$\in D$ ***do***
$I_{i,j} = rand(0,1)$
end for
$Fit_i = f(I_i)$
end for
 	
While (t<=Max) do
 	
for each $i \in N$ ***do***
$P_1, P_2 =$ ***Procreate(***I_i, I_j)
P′ = Cannibalism (P_1, P_2)
P''= ***Mutate(P′***)
for each j $\in D$ ***do***
$P', P'' = (if(P_j', P_j'') > 0.5,1,0)$
end for
If ($f(P'') < f(P_i)$) *the**n***
$I_i = P''$
Elseif ($f(P'') < f(P_j)$) ***then***
$I_j = P''$
End if
End for
End while

Output: Potential positions

Algorithm 1: BWO - m Connected Coverage for finding potential positions

Experimental results and Discussions

Using MATLAB version 8.3, the modelling setup for the suggested method was put into practice using a machine that included an Intel Core i7 processor running at 3.2 GHz, 4GB of RAM, and Windows 10. To ensure the ease of simulating the area, the system has been maintained in an inactive state with basic utility features. The suggested approach has been evaluated under two simulated settings. Two distinct situations were conducted to evaluate the suggested method. The first grid simulates a territory with a total area of 50x50 square meters, while the second grid represents a location with an expanded area of 100x100 square meters. The base station is positioned at coordinates 25x50 in the first grid, and at coordinates 50x100 in the second grid.

Performance Measures:

A. *Computational Time:* The term "Computation time" refers to the duration required to successfully execute a certain quantity of repetitions.

B. *The quantity of sensor nodes in use:* This ratio describes how many sensor nodes are installed in relation to all available sites.

C. *F value:* The F value represents the proportion of available spots for sensor node placement to the overall several deployed sensor lumps.

$$F = \frac{K}{L}$$

Let K represent the aggregate quantity of available sites for the placement of sensors, whereas L denotes the total count of sensors that have been deployed. The MATLAB simulation zone consists of a grid of 50x50 square meters.

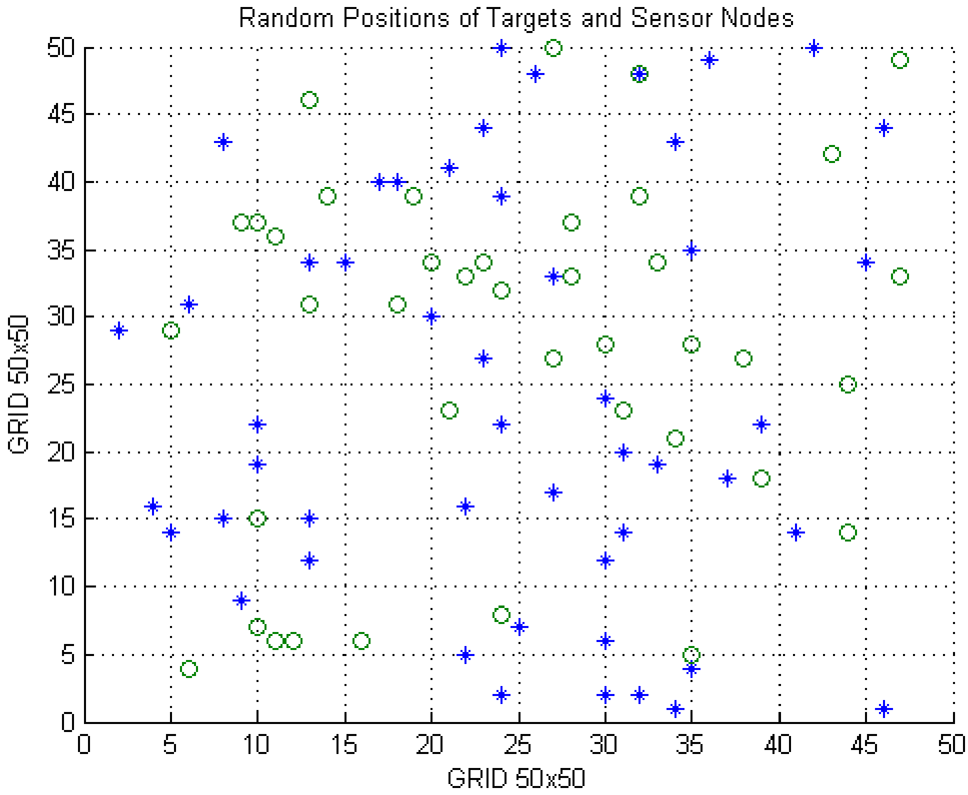


Fig. 3. 50X50 GRID

o – Sensor Nodes * - Targets

The simulation zone consists of a 50x50 grid, including forty sensor nodes and fifty randomly selected targets in total. The table below displays the resulting data.

Table 1. Simulation Results of Grid 50X50

Algorithms	Comp. Time (s)	No. of Nodes Organized	F-Value
GA	6.394942	30	2.210314
PSO	5.767097	26	2.090247
BWO	5.210509	19	2.887575

The graphic below depicts the distribution of the total amount of nodes placed during 100 repetitions in a 50x50 grid

Fig.4. Comparison of optimal results w.r.t. iterations for 50X50 GRID

The MATLAB imitation area consists of a grid of 100x100 square meters.

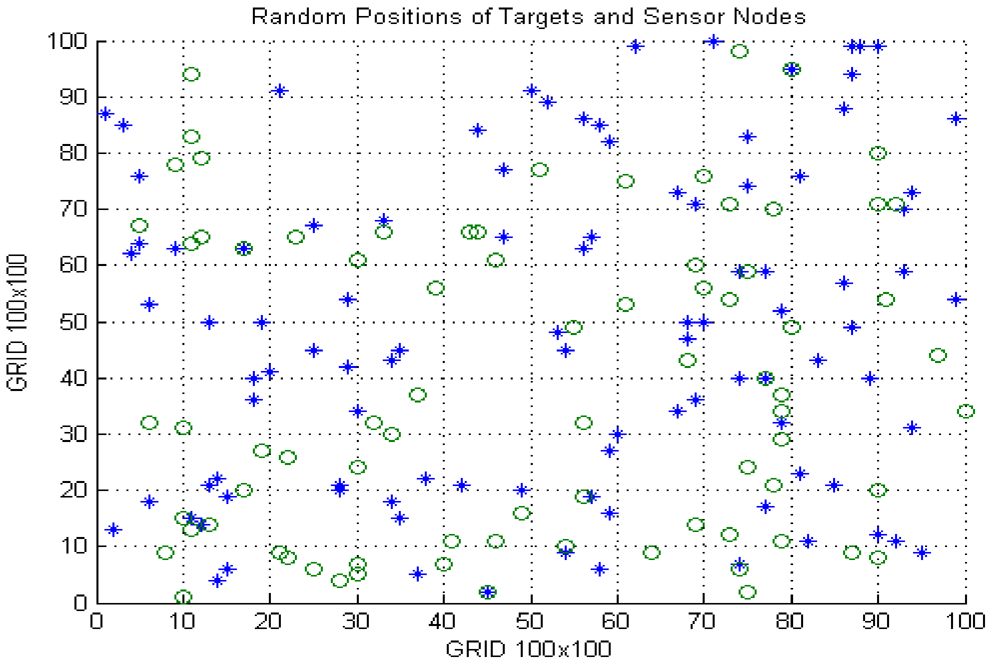


Fig. 5. 100X 100 GRIDS

o – Sensor Nodes * - Targets

The following table presents the presentation metrics of the GA, PSO, and BWO.

Table 2. Simulation Results of Grid 100X100

Algorithms	Comp. Time (s)	No. of Nodes Deployed	F-Value
GA	9.253804	53	2.116093
PSO	7.69367	48	1.910142
BWO	7.075379	42	1.969632

According to Tables 2 and 3, it can be seen that our suggested strategy has superior performance compared to the current approaches.

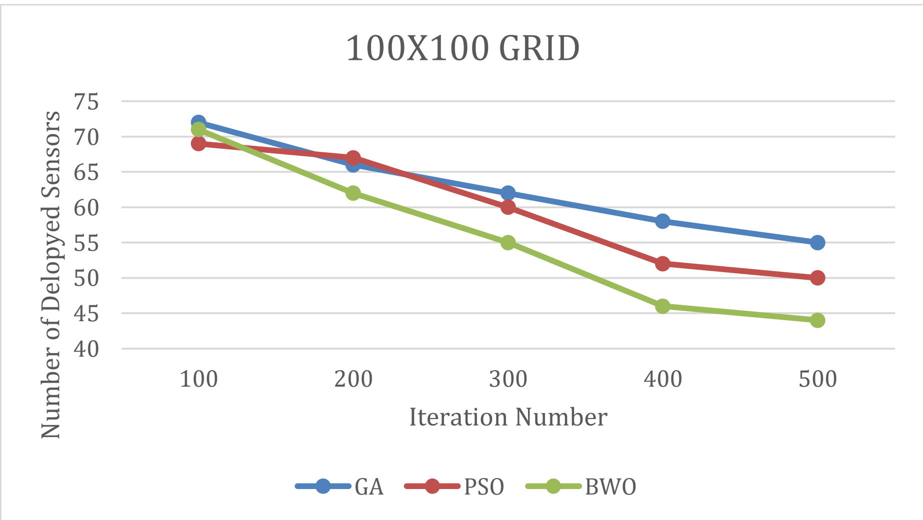


Fig. 6. Evaluation of the best outcomes in terms of cycles for 50X50 GRID

5. Conclusion

When utilized in sensitive applications, IoT requires a high level of connection and coverage. In this study, we provide a proposed methodology for scheduling sensor nodes in a manner that ensures both connection and coverage requirements are satisfied, while minimizing the number of active sensor nodes. Consequently, this results in an extended duration of network functionality. The necessity for employing such a technique arises in situations where it is not required to monitor all targets at the same level of proximity. In order to guarantee the accuracy of the data gathered and to facilitate its distribution to other the nodes, particularly the base station, it is also crucial for the activated nodes to establish m-connectedness. It is observed that the introduction of connection has a little impact on the overall network lifespan. This research employs the Metaheuristic Black Widow Optimization Algorithm to address the challenge of solving a m linked coverage IoT network. The Introduction part provides a comprehensive description of the subject, while part 3 presents a mathematical definition of the provided problem. The proposed methodology's results have been juxtaposed with those of earlier evolutionary techniques, specifically Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO). The results show that when compared to the existing approaches, the new algorithm performs better. This study has the potential to be further developed because it can handle the m connected k coverage problem.

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