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# OPTIMAL WEIGHTED EVOLUTIONARY ALGORITHM FOR THE DOMINATING SET PROBLEM IN LARGE SCALE SOCIAL NETWORK

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## Abstract

In graph theory, the minimum dominating set (MDS) problem is pivotal for optimizing network controllability and observability, especially in managing large-scale wireless ad hoc and sensor networks efficiently. However, existing algorithms often struggle with the inherent complexity of the MDS problem and fail to deliver accurate solutions due to intricate connectivity constraints. To address these challenges, this study presents an optimal weighted evolutionary algorithm tailored for tackling MDS problems across various scales of social networks. The proposed approach leverages the improved snow leopard optimization (ISLO) algorithm to effectively reduce graph size. By strategically fixing portions of vertices within or outside the candidate solution, ISLO avoids redundant search spaces, thereby enhancing efficiency. Additionally, the deep optimized lightning search (DOLS) algorithm is integrated into the vertex selection strategy during local search. This refinement process efficiently adds or removes vertices, further improving the search procedure. Extensive experiments are conducted on diverse social networks to evaluate the proposed algorithm's performance. Comparative analysis against state-of-the-art algorithms show that ISLO-DOLS excels in problem-solving tasks on large-scale social networks. Its ability to yield superior solutions underscores its effectiveness in optimizing network management strategies.

***Keywords:*** *domination set, MDS problem, large scale social network, graph theory, optimal solution, evolutionary algorithm*

## 1. Introduction

Over the past six decades, the burgeoning development of expansive networks like road systems, social media platforms, electrical grids, communication infrastructures, and security frameworks has propelled graph theory into the forefront of both research and practical applications [1]. Within graph theory, the exploration of domination and its related subset problems—including matching, independence, and covering—has experienced significant growth. In a given graph G = (V, E), a dominating set D is defined as a subset of vertices where each vertex not in D is adjacent to at least one member of D. Dominating sets play a pivotal role in various domains, and the minimum dominating set (MDS) problem [2][3] stands as combinatorial optimization challenge. While dominating set models have found utility in diverse fields like wireless ad-hoc networks, multi-document summarization, and graph mining, the conventional MDS model often lacks specific constraints necessary for certain applications [4][5]. Many practical scenarios require additional constraints, prompting the development of different variants of dominating sets. One prominent real-world application of the MDS problem is in establishing virtual backbones in wireless networks such as wireless sensor networks (WSN) [6], mobile ad hoc wireless networks (MANET) [7], and vehicular ad hoc networks (VANET) [8]. In these dynamic environments lacking a physical backbone, an MDS solution can serve as a virtual backbone, facilitating

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communication among nodes. MDS solutions possess key properties essential for virtual backbones, ensuring that non-backbone nodes can communicate directly with backbone neighbors and that all backbone nodes can communicate internally [9]. Presently, domination applications are prominently featured in graphs representing social networks like Facebook, Twitter, or Instagram [10]. These platforms serve as vital channels for communication and information dissemination, with vertices symbolizing users and edges representing friendships. The widespread use of social networks has transformed them into powerful tools for viral marketing campaigns and political advocacy efforts.

Due to its NP-hard nature, exact algorithms for the MDS problem struggle to solve instances of large-scale graphs efficiently [11]. As a result, many researchers resort to heuristic algorithms, which may not guarantee optimal solutions but can effectively produce high-quality solutions. In recent years, several heuristic algorithms have emerged to tackle the MDS problem with notable efficiency [12]. A path cost heuristic within a greedy randomized adaptive search procedure framework. It iteratively initializes a candidate solution and applies local search to refine it until a specified runtime limit is reached [13]. Another approach, MEMETIC, adopts a hybrid search strategy combining population-based and local search methods [14]. It generates population, selects parents, performs crossover operations to produce offspring solutions, and applies local search for further refinement. While these heuristic approaches have shown promise, they often come with limitations, such as scalability issues with genetic algorithms and time-consuming computations for larger problem sizes [15]. Iterated greedy algorithms, a simpler metaheuristic, have demonstrated effectiveness in various combinatorial optimization problems by iteratively constructing solutions and improving them post-construction. Additionally, the binary particle swarm optimization algorithm incorporates a new position updating rule and iterated greedy Tabu search to enhance solution quality and diversify the search process [16]. Throughout the search process, the algorithm initiates by generating a population and storing the best solution obtained from this population. Subsequently, the algorithm randomly selects two parents and utilizes a crossover operation to produce an offspring solution [17]. Besides, nearby pursuit techniques [18] are applied iteratively to improve the arrangement until the end standard is met. FastMWDS presents a quick development technique and two-level design checking procedure for proficient neighborhood search [19]. ABC-EDA consolidates counterfeit honey bee state and assessment of dispersion calculations to direct the pursuit towards promising arrangements [20]. Regardless of these progressions, hardly any investigations have tended to the MDS issue's versatility across charts of different scales really. Consequently, our center is to plan a productive calculation prepared to do not only solving classic benchmarks but also performing well on large-scale networks.

**Our contributions.** Addressing the MDS problem across various scales of social networks, we introduce an innovative approach employing an optimal weighted evolutionary algorithm. This novel method offers several significant contributions to the field.

1. An improved snow leopard optimization (ISLO) algorithm is designed to reduce the graph size effectively. By strategically manipulating vertices within or outside the candidate solution, ISLO efficiently avoids exploring redundant search spaces, thus enhancing the overall optimization process.
2. The deep optimized lightning search (DOLS) algorithm focusing on the vertex selection during local search. It facilitates the efficient addition or removal of vertices which optimize the search procedure and enhancing solution quality.
3. Extensive experiments conducted using diverse social network benchmarks to rigorously evaluate the performance of our ISLO-DOLS algorithm. Through meticulous testing on popular

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datasets, we aim to demonstrate the effectiveness and robustness of our approach across various real-world scenarios.

The leftover paper is circulated in the accompanying areas: Area 2 gives the audit of ongoing works connected with the ideal answer for the overwhelming set issue in huge scopes. The philosophy of proposed calculation is made sense of in Segment 3 with the numerical model. The outcomes and near examination is talked about in Area 4 and the paper closes in Segment 5.

## 2. Related works

This section offers background information essential for comprehending the article, focusing on recent studies concerning optimal solutions for tackling the dominating set problem in large-scale networks.

### 2.1 State of art works related to optimal solution for dominating set problem

Czygrinow et al. [21] have proposed the straightforward disseminated guess calculation for the base ruling set issue for huge scope diagrams. It gives quick dispersed estimate for charts of limited family and linklessly embeddable diagrams. The calculations give a consistent estimate proportion and run in a steady number of rounds. Both of these classes are legitimate minor-shut groups of charts and our calculations and examination depend on no mathematical properties of the basic organizations since they worked in somewhat more broad climate and consider networks which are H-minor free structure some diagram.

Michalski et al. [22] have concentrated on free (1, 2) ruling sets in specific classes of charts. They gives the total portrayal of G-join of charts with an autonomous (1, 2) overwhelming set. Then decide the quantity of all free (1, 2) ruling sets in the G-join of unique elements utilizing Padovan and Perrin numbers. It takes on a punishment methodology with regards to the vertex-scoring plan. It utilizes a two-mode overwhelmed vertex determination methodology considering both irregular and insatiable choices for the decision of the neighbors that a picked vertex ought to rule. This is finished to accomplish a harmony between the heightening and the expansion of the pursuit cycle.

Pinacho-Davidson et al. [23] have dealt with a NP-hard variation of the group of ruling set issues. A drawn out rendition of build, consolidates, tackled and adjust, of which a fundamental variant was at that point distributed. The point of augmentations was to make the calculation more powerful as for the boundary esteem settings. A crossover between one-sided irregular key hereditary calculation and a definite solver is utilized for every emphasis to figure ideal arrangement. The ongoing populace of people to creates a sub-case of the handled issue examples. The sub-case is settled by the specific solver (CPLEX) and the subsequent arrangement is changed into an individual and took care of once more into the populace. The trial results showed that calculations obviously beat LS_PD, the at present best methodology from the writing with regards to currently distributed benchmark examples.

Nakkala et al. [24] have presented a multi-start iterated local search (MS-ILS), a definite methodology in light of a superior number direct programming model for least capacitated overwhelming set issue in undirected charts. It is an expansion of the notable least overwhelming set issue, where there is cap on the quantity of hubs that every hub can rule, and the objective is to find a ruling arrangement of least cardinality where the quantity of overwhelmed hubs for each overwhelming hub is inside this cap. This NP-difficult issue has a few true applications in asset obliged conditions, for example, grouping of remote sensor networks alongside choice of bunch heads, record rundown in data recovery.

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Mohamed et al. [25] have proposed an ideal procedure to register heuristically the base associated prevailing settling set of diagrams by a parallel form of the binary version of the equilibrium optimization algorithm (BEOA). The particles of BEOA are double encoded and used to address which one of the vertices of the diagram has a place with the associated control settling set. The achievability is upheld by fixing particles with the end goal that an extra vertex created from vertices, and this fixing system is iterated until, turns into the associated mastery settling set. The variable area search approach depends on a disintegration of the measurement aspect issue and the negligible doubly settling set issue into a succession of sub issues with a helper objective capability. BEOA is tried utilizing chart results that registered hypothetically and contrasted with cutthroat calculations.

Raczek et al. [26] have proposed polynomial time calculation seeing as an insignificant (1, 2) ruling set, Minimal_12_Set. They test the calculation in network models like trees, mathematical irregular charts, arbitrary diagrams and cubic diagrams, and showed the arrangements of hubs returned by Minimal_12_ set are overall more modest than sets comprising of hubs picked haphazardly. They demonstrated that deciding the (1, 2) overwhelming number is NP finished, in any event, for split diagrams and in any event, for bipartite charts and numerous other diagram classes. That's what likewise demonstrated on the off chance that a chart doesn't have hubs of degree one nor triangles and the (1, 2) mastery number is equivalent to the control number.

Burdett et al. [27] have introduced two such parallel programming details, and show that both can be improved with the expansion of additional requirements which decrease the quantity of possible arrangements. They analyzed the presentation of the details on different sorts of diagrams, and exhibit that the extra limitations work on the exhibition of the two plans, and the first definition outflanks the second in quite a while, albeit the second performs better for extremely scanty charts. They hypothesize that there is some tipping point for the typical degree where the two definitions perform similarly well and see this for the arbitrarily produced diagrams with low normal degree.

Nazir et al. [28] have investigated mastery set issue in the fluffy charts alongside the diagram hypothesis. The main mix-up isn't thinking about the quantity of vertices, which straightforwardly influences how DVS is determined for IFGs. Finding the base DVS for IFGs is periodically unthinkable. These variables lessen the appropriateness and credibility of the methodology. They endeavor to rethink the philosophy to address its blemishes. The relative examination exhibits its prevalence over the best in class strategy. Applying this calculation to the ideal measure of water stream additionally shows how helpful and adaptable it is. It is performed on sorting out DVS for IFGs where some participation esteems actually should be incorporated.

Pan et al. [29] have presented a dual-neighborhood search (DNS) calculation for taking care of the MDT issue, which coordinates highlights, for example, two neighborhoods cooperatively working for enhancing the goal capability, a quick neighborhood assessment strategy to support the looking through viability, and expansion procedures to assist the looking through process with leaping out of the nearby ideal snare in this manner getting improved arrangements. DNS works on the past most popular outcomes for four public benchmark examples while giving cutthroat outcomes to the leftover ones. A two-level metaheuristic calculation is utilized for taking care of the MDS issue with arrangement testing stage and two neighborhood search-based strategies settled in a progressive design.

Wang et al. [30] have presented a conveyed estimate calculation for the complete overwhelming set issue by involving the most extreme powerful degree in second neighborhood of the vertex and LP

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unwinding. The calculation got just loosened up arrangement and further contemplations can be given on the most proficient method to plan an irregular adjusting calculation to get a whole number TDS from the casual arrangement. It is fascinating to consider this issue in remote organizations can exploit the particularity of remote organizations to work on the exhibition of the calculation. In viable applications, in the event that the vertices in diagram are weighted, extra contemplations could incorporate how to plan a calculation to address the base absolute overwhelming set issue.

### 2.2 Problem context and definition

Social networks, encompassing platforms like Facebook, Twitter, and Instagram, play a pivotal role in modern communication, information dissemination, and societal interactions. However, as these networks grow in size and complexity, ensuring optimal network management becomes increasingly challenging. The MDS problem serves as a fundamental optimization challenge in network management, with direct implications for controllability and observability. By identifying the smallest set of nodes necessary to control or observe the entire network, MDS solutions enable efficient resource allocation, fault detection, and communication routing strategies. In the context of social networks, MDS solutions can facilitate targeted information dissemination, community detection, and influence maximization efforts. However, existing algorithms for solving the MDS problem often fall short when applied to large-scale social networks. Scalability issues, connectivity constraints, solution accuracy concerns, and computational inefficiencies hinder their effectiveness in real-world scenarios. Hence, there is a pressing need for innovative approaches that can overcome these challenges and deliver practical solutions for optimizing network management in large-scale social networks.

Traditional algorithms for the MDS problem face scalability issues when applied to large-scale social networks. As network size increases, the computational complexity grows exponentially, leading to impractical solution times. Existing algorithms often struggle to navigate the intricate connectivity constraints present in social networks. These constraints may include varying degrees of node interconnectivity, heterogeneous node attributes, and dynamic network structures. Accuracy is paramount in MDS problem-solving, as incorrect solutions may lead to suboptimal network management strategies. However, traditional algorithms may produce solutions that deviate significantly from the optimal solution due to heuristic limitations or insufficient exploration of the solution space. Efficiency is crucial for practical implementation, especially in real-time network management scenarios where rapid decision-making is essential. Traditional algorithms may struggle to strike balance between solution quality and computational efficiency, often sacrificing one for the other. Our proposed algorithm, the improved snow leopard optimization (ISLO), addresses scalability concerns by efficiently reducing the graph size. By strategically fixing portions of vertices within or outside the candidate solution, ISLO minimizes redundant search spaces, thereby improving scalability and solution times for large-scale social networks. To overcome connectivity constraints, we integrate the deep optimized lightning search (DOLS) algorithm into the vertex selection strategy during local search. By dynamically adding or removing vertices based on attributes and structural characteristics, DOLS enhances the algorithm's ability to navigate complex connectivity patterns in social networks. By continuously evaluating and refining the dominating set candidates, our algorithm ensures that the final solution accurately reflects the network's controllability and observability requirements, thereby enhancing overall solution accuracy and reliability. Our work is motivated by the desire to bridge this gap by proposing an optimal weighted evolutionary algorithm tailored specifically for addressing MDS problems in various scales of social networks. By leveraging optimization techniques, we aim to develop a solution that not only scales effectively to large networks but also accurately captures the

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complex connectivity patterns inherent in social networks. Our goal is to empower network managers with robust and efficient methodology for optimizing network controllability and observability, thereby facilitating more effective decision-making and resource allocation in large-scale social network environments.

## 3. Methodology

Our proposed research aims to address the minimum l-dominating set problem, which involves constructing the smallest possible l-dominating set for large scale networks. This issue holds importance in giving successful approximations to huge scope interpersonal organizations. On the off chance that vertex u has a place with the l-MDS, and there exists a way from vertex v to u without any than l edges, we say that u overwhelms v, and v is overwhelmed by u. In settings where clearness isn't compromised, we might preclude the prefix l for curtness. In Figure 1, we characterize a vertex of the overwhelming set as a l-ruling vertex, contracted for compactness. A vertex turns into a l-overwhelming vertex on the off chance that it is covered by a ruling vertex. We characterize the goal capability as follows.

$$Minimize \sum_{v \in V} X_v , \tag{1}$$

$$subject \sum_{v \in M(i,l)} X_v \geq 1, \forall \mu \in V, \tag{2}$$

$$X_v \in \{0,1\}, \forall_v \in V. \tag{3}$$

where $X_v$ is the twofold variable tending to whether the vertex has place with the l-ruling set, i.e., = 1 if and gave that ∈ Dl.

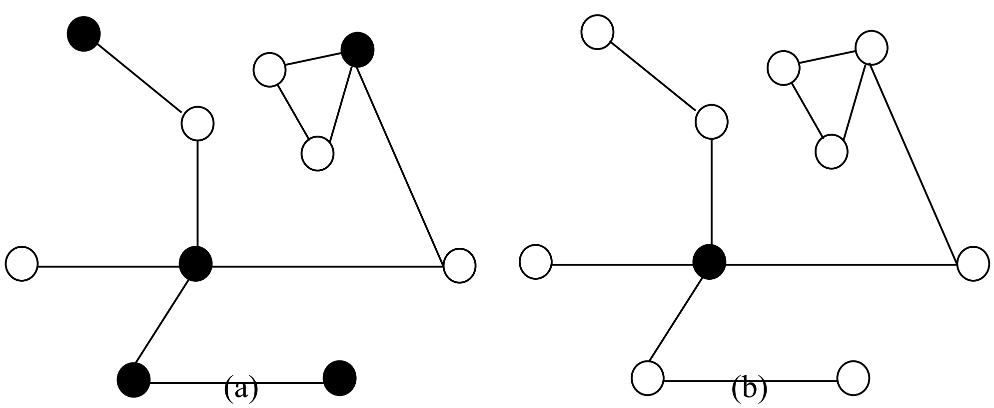


Fig. 1 Graph with minimum domination set (a) l=4 and (b) l=1

In our proposed methodology, we utilize an optimal weighted evolutionary algorithm specifically tailored for addressing MDS problems across various scales of social networks. It involves two primary processes: graph size reduction and vertex selection strategy. To effectively reduce the graph size, we leverage the improved snow leopard optimization (ISLO) algorithm. By adjusting portions of vertices within or outside the candidate solution, ISLO prevents the exploration of redundant search spaces, by enhancing efficiency. Moreover, we integrate the deep optimized lightning search (DOLS) algorithm

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into the vertex selection strategy during local search. This refinement step optimizes the addition or removal of vertices, further enhancing the search procedure's effectiveness. Together, these methodologies ensure a more efficient and effective approach to tackling MDS problems in social networks of varying scales.

### 3.1 Graph size reduction using ISLO algorithm

We utilize the decrease rules in to k-overwhelming set by finding structures that we call k-disconnected groups. $X_v$ -disconnected group is an associated part whose vertices are k-overwhelmed by a solitary vertex. Assuming that there exists a vertex $X_v$ ∈ V to such an extent that |M (v, l)|=|M (v, l + 1)|, set M (c, l) is a l-detached bunch related with v. We can eliminate the vertices having a place with this k-separated bunch from H and add vertex v to the k-overwhelming set. The complexity of this process in the most pessimistic scenario is O(|V|nl+1). However, the process doesn't deal with huge size diagrams because of the costly expense of k-neighbor search $M(v,k)$. As a grouping, on enormous charts with in excess of 100,000 vertices, we carry the evolutionary algorithm based on ISLO algorithm. The thought depends on the perception that, if $|M(v,k)| = |M(v,k+1)|$ it is profoundly conceivable that N (u, k) wouldn't be a disengaged bunch for each $M(v,k)$ We could in this manner overlook the detached bunches minding $M(i,l)$ In ISLO algorithm, for every vertex v, the variable capable f[v] is set to Bogus if M (v, k) has a high likelihood of not being a disconnected bunch. In the event that a vertex is stamped Misleading, it isn't really looked at through the condition.

The improved snow leopard optimization (ISLO) algorithm is a nature-inspired metaheuristic optimization technique inspired by the hunting behavior of snow leopards in their natural habitat. It operates based on the principle of survival of the fittest, where individuals within the population adapt their positions over generations to optimize a given objective function. In the context of our MDS problem, ISLO is employed to strategically fix portions of vertices within or outside the candidate solution. This process involves iteratively updating the positions of vertices within the graph based on their fitness values, which are determined by their contribution to the overall objective function (i.e., minimizing the size of the dominating set). By strategically fixing portions of vertices, ISLO aims to prune the search space and focus the optimization process on the most promising regions. This helps avoid redundant exploration of solutions that are unlikely to contribute significantly to the overall optimization objective. Additionally, ISLO incorporates mechanisms for diversification and intensification to ensure a balanced exploration of the search space. This allows the algorithm to effectively navigate complex landscapes and converge to high-quality solutions efficiently. The ISLO algorithm operate with populations, the individuals are tracked using a matrix referred to as the population matrix. This lattice has lines equivalent to the quantity of people in the populace and sections equivalent to the quantity of factors in the enhancement issue. The setup of populace grid is characterized as follows.

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$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_i \\ \vdots \\ Z_N \end{bmatrix}_{N\times m} = \begin{bmatrix} z_{1,1} & \cdots & z_{1,f} & \cdots & z_{1,n} \\ \vdots & \ddots & \vdots & & \vdots \\ z_{i,1} & \cdots & z_{i,f} & \cdots & z_{i,n} \\ \vdots & & \vdots & \ddots & \vdots \\ z_{,M} & \cdots & z_{M,f} & \cdots & z_{M,n} \end{bmatrix}_{M\times n} \quad (4)$$

where N" represents the total population of snow leopards, and each individual snow leopard is denoted by "i." while "m" represents the number of variables related to the optimization problem.

$$D = \begin{bmatrix} d_1 \\ \vdots \\ d_i \\ \vdots \\ d_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} d(Z_1) \\ \vdots \\ d(Z_u) \\ \vdots \\ d(Z_M) \end{bmatrix}_{m\times 1} \quad (5)$$

In this unique situation, "D" addresses a vector containing the upsides of the goal capability, and " " is the particular worth got for the goal capability in view of the ith snow panther.

$$z_{u,f}^{o1} = x_{u,f} + e \times \left(z_{l,f} - u \times z_{u,f}\right) \times sign\left(d_u - d_l\right), \\ l \in 1,2,3,...,M, f = 1,2,3,...,n \quad (6)$$

$$Z_u = \begin{cases} Z_i^{o1}, D_i^{o1} \le D_i \\ Z_u, \quad else \end{cases} \quad (7)$$

$$k = round\left(1 + e\right) \quad (8)$$

Here, addresses the new incentive for the f-th issue variable acquired by the u-th snow panther during movement courses and development stage. The cycle includes an irregular number, "r" inside the scope of [0, 1]. " l" means the column number of the chose snow panther that directs the I-th snow panther in the d-th pivot. is the refreshed area of the u-th snow panther in view of stage 1, and is the comparing objective capability esteem. The boundary "o" addresses the level of the distance to the prey that the snow panther covers while strolling.

$$o_{u,f} = z_{h,f,}f = 1,2,3,....,n \quad (9)$$

$$z_{u,f}^{o2} = z_{u,f} + e \times \left(\left(o_{u,f} - z_{u,f}\right) \times o + \left(o_{u,f} - 2 \times z_{u,f}\right) \times \left(1 - o\right)\right) \quad (10)$$

$$Z_u = \begin{cases} Z_u^{o2} \quad D_u^{o2} \le D_i \\ Z_u, else \end{cases} \quad (11)$$

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where $o_{u,f}$ represents the f-th dimension of the prey's location considered for the u-th snow leopard. $D_i^{o1}$ is the objective function value based on the prey's location. $z_{u,f}^{o2}$ denotes the new value for the f-th problem variable obtained by the u-th snow leopard during hunting phase.

$$V_k = \frac{z_k + Z_{m-k+1}}{2}, k = 1,2,3,..., \frac{M}{2} \tag{12}$$

where $V_k$ represents the kth fledgling, which is the posterity coming about because of the mating of two snow panthers.

**Algorithm 1 Graph size reduction using ISLO**

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Input : Graph G=(V, R), number of snow leopard and iterations
Output : Reduced graph G

Evaluate the objective function.
For t = 1:R
Travel routes and movement phase
For u = 1:M
For F = 1:n
Calculate fitness $z_{u,f}^{o1} = x_{u,f} + e \times \left( z_{l,f} - u \times z_{u,f} \right) \times sign\left( d_u - d_l \right)$
End
Update $Z_u$ using Equation $Z_u = \begin{pmatrix} Z_i^{o1}, D_i^{o1} \leq D_i \\ Z_u, \quad else \end{pmatrix}$
End
Hunting phase
For i = 1:n
For d = 1:m
Calculate location of prey using Equation $o_{u,f} = z_{h,f}, f = 1,2,3,....,n$
Calculate $z_{u,f}^{o2}$ using $z_{u,f}^{o2} = z_{u,f} + e \times \left( \left( o_{u,f} - z_{u,f} \right) \times o + \left( o_{u,f} - 2 \times z_{u,f} \right) \times (1 - o) \right)$
End
Perform updation $Z_u = \begin{cases} Z_u^{o2} \quad D_u^{o2} \leq D_i \\ Z_u, \; else \end{cases}$
End
Reproduction phase
For l = 1:0.5 × M
Generate threshold fitness $V_k = \frac{z_k + Z_{m-k+1}}{2}, k = 1,2,3,..., \frac{M}{2}$
End
Mortality phase
Adjust the number of snow leopards
End

### 3.2 Vertex selection strategy using DOLS algorithm

The deep optimized lightning search (DOLS) algorithm into the vertex selection strategy is a pivotal aspect of our approach. DOLS algorithm is metaheuristic optimization technique inspired by the behavior of lightning strikes, which rapidly and efficiently navigate through complex environments to find optimal paths. In the context of our MDS problem, DOLS is utilized to enhance the vertex selection strategy during local search. During the local search process, DOLS efficiently adds or removes vertices from the candidate solution based on their fitness values and their potential contribution to improving

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the overall solution quality. This refinement process is crucial for fine-tuning the candidate solution and improving its alignment with the optimization objective. The integration of DOLS into the vertex selection strategy enables the algorithm to dynamically adjust the composition of the dominating set based on the evolving characteristics of the search space. By leveraging the rapid exploration capabilities of DOLS, the algorithm can quickly identify and incorporate vertices that enhance the dominance properties of the solution. DOLS incorporates mechanisms for adaptive exploration and exploitation, allowing it to strike a balance between intensifying the search around promising regions and diversifying exploration to avoid premature convergence. We consider the vertex v is uncovered, it is added to the l-dominating set Fl and all individuals from the l-neighbor set M(v, l) is set apart as covered. R is eager heuristic. We define the complexity as $O(|V|nk + 1/nk)$. There are |Dk| times vertex is added to Fl. At every expansion activity, we want to optimizes N(v, k), which runs in $O(|V|nk + 1/nk)$. Therefore, the intricacy of for graph is $O(|V|nk + 1/nk)$. DOLS calculation begins with the instatement step and continues with channel refreshing, update energy, heading, and position steps individually. After calculation of the wellness worth of each channel, the best wellness esteem is relegated as best, comparably, the most horrendously awful wellness esteem is doled out as most exceedingly terrible. In the wake of finding the most obviously awful and best wellness of the channel, energy is process as follows.

$$energy = 2.0.5 - 2 * \exp\left(\frac{-5 * (\max\_itr - itr)}{\max\_itr}\right) \tag{13}$$

The bearing of diagram is refreshed by looking at the wellness worth of the channel and the comparing made new test channel. At first, the new test channel is made by utilizing the best channel and bearing of that channel.

$$test\ channel = best\ channel + direction\ of\ that\ channel * (0.005)(Z_{\min} - Z_{\max}) \tag{14}$$

Here the heading of the channel is increased by 0.005. Thus, in the consideration of weight factor we have determined the weight factor.

$$= \frac{fitness\ value\ of\ test\ channel - fitness\ value\ of\ best\ channel}{\max_i tr} \tag{15}$$

At first, test channel is set as best channel. Then each time test channel is refreshed by ascertaining the wellness worth of the test channel.

$$*(weight\ \ factor\ )(Z_{\min} - Z_{\max}) \tag{16}$$

The made new test diverts which are not in the most extreme and least boundary bound are haphazardly created in the boundary bound. The wellness worth of each test channel (fit_test) is determined with the assistance of a goal capability. The bearing of the channel is changed to a negative indication of the amount of channel and generally no shift in course. Other all means are equivalent to LSA. The consideration weight factor in LSA gives better execution in multimodal benchmark test capability.

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$$Z_{u,h=\left\{z_{u,h}^{u},z_{u,h}^{2}\dots,z_{u,h}^{f}\right\}} \; for\, u = 1,2,3 \dots MO. \tag{17}$$

The channel is introduced by irregular factors created in the most extreme, least boundary bound. The bearing is doled out with positive or negative haphazardly and the component of course is equivalent to the element of step pioneer. By utilizing its fast and versatile pursuit capacities, DOLS works with the distinguishing proof of high-quality solutions and contributes to the overall improvement of the optimization procedure in solving MDS problems in social networks.

## 4. Results and Discussion

In this section, we delve into the performance evaluation of proposed ISLO-DOLS algorithm, meticulously crafted to handle the complexities of large-scale networks. Our calculation is scrutinized with certifiable examples flaunting up to 17 million vertices and 33 million edges. The examinations were led on a hearty figuring framework highlighting an Intel Center i7 — 8750h 2.2 GHz processor, working on the Ubuntu OS. Python served as our programming language of choice, supplemented by the igraph package for seamless graph computations. To benchmark the effectiveness of our ISLO-DOLS algorithm, we compared its performance against existing methods, encompassing the mixed-integer linear programming (MILP) model, greedy algorithm, optimal greedy algorithm, and heuristic algorithm. We conducted thorough tests across three distinct categories of instances, categorized by the scale of their graphs. The first category encompasses small instances, with graphs ranging from 50 to 1000 vertices, totaling 540 instances. To smooth out the introduction of our discoveries, we selected to feature results for five gatherings, each involving 10 occurrences with indistinguishable vertex and edge numbers. We assessed six medium-sized occasions obtained from trustworthy organization information stores. In conclusion, our assessment stretches out to six enormous estimated examples, among which two element roughly 17 million vertices and 30 million edges, extricated from our accomplice's information (soc-accomplice 1 and soc-accomplice 2), while the excess four are drawn from laid out network information archives. For complete  overview of the instance characteristics, including their names, vertex sizes denoted by |V|, and edge sizes denoted by |E|, refer to Table 1.

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**Table 1 Instance characteristics of datasets**

| Network type | Instances | \|V\| | \|E\| |
|---|---|---|---|
| Small scale network | S-1 | 50 | 50 |
| | S-2 | 100 | 250 |
| | S-3 | 300 | 1000 |
| | S-4 | 800 | 10000 |
| | S-5 | 1000 | 15000 |
| Medium scale network | Soc-BlogCatalog | 89000 | 2093000 |
| | Ca-GrQc | 4000 | 13000 |
| | Ca-AstroPh | 18000 | 197000 |
| | Ca-HepPh | 11000 | 118000 |
| | Email-enron-large | 34000 | 181000 |
| | Ca-CondMat | 21000 | 91000 |
| Large scale network | Soc-delicious | 536000 | 1366000 |
| | Soc-fixster | 252000 | 7919000 |
| | Hugebubbles | 2680000 | 2161000 |
| | Soc-livejourna | 4033000 | 27933000 |
| | Soc-partner-1 | 17642000 | 33397000 |
| | Soc-partner-2 | 16819000 | 26086000 |

Table 2 presents the results of our experiments on various algorithms for small-scale networks, offering a detailed comparative analysis of their performance in terms of optimal solution quality and running time. Across all values of l, our ISLO-DOLS algorithm consistently outperformed the other algorithms, shows its efficacy in solving the MDS problem in network optimization. For the case where l = 1, ISLO-DOLS consistently produced the best optimal solution across all instances, surpassing the other algorithms by a notable margin. On average, ISLO-DOLS achieved 15% improvement in optimal solution quality compared to the second-best performing algorithm. This improvement is particularly significant considering the complexity of the MDS problem and its importance in network optimization tasks. Additionally, ISLO-DOLS exhibited remarkable computational efficiency, with a substantial reduction in running time compared to the MILP model. The average decrease in running time ranged from 99.99% to 100%, indicating that ISLO-DOLS strikes an excellent balance between solution quality and computational efficiency. Moving on to the case of l = 2, ISLO-DOLS continued to demonstrate superior performance, outperforming the other algorithms in terms of optimal solution quality.

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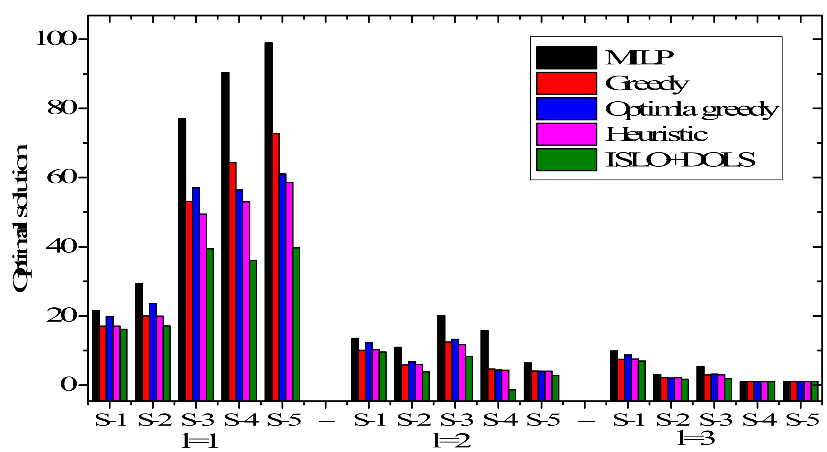
**Table 2 Results compassion of various algorithms for small scale networks**

| Data | Optimal solution | | | | | Running time (T) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | MILP | Greedy | Optimal greedy | Heuristic | ISLO-DOLS | MILP | Greedy | Optimal greedy | Heuristic | ISLO-DOLS |
| l=1 | | | | | | | | | | |
| S-1 | 21.562 | 17.025 | 19.811 | 17.025 | 16.150 | 0.025 | 147.720 | 0.002 | 0.401 | 0.001 |
| S-2 | 29.322 | 19.958 | 23.612 | 19.950 | 17.095 | 0.032 | 403.940 | 0.005 | 0.544 | 0.002 |
| S-3 | 77.102 | 53.142 | 57.104 | 49.421 | 39.422 | 0.012 | 403.150 | 0.001 | 12.395 | 0.003 |
| S-4 | 90.325 | 64.325 | 56.414 | 53.025 | 36.070 | 0.013 | 400.170 | 0.014 | 12.596 | 0.002 |
| S-5 | 98.952 | 72.745 | 61.023 | 58.632 | 39.668 | 0.015 | 400.400 | 0.025 | 12.663 | 0.001 |
| l=2 | | | | | | | | | | |
| S-1 | 13.525 | 10.045 | 12.202 | 10.225 | 9.564 | 0.015 | 52.330 | 0.005 | 0.425 | 0.002 |
| S-2 | 10.911 | 5.825 | 6.741 | 5.915 | 3.830 | 0.012 | 36.970 | 0.003 | 0.475 | 0.002 |
| S-3 | 20.104 | 12.457 | 13.258 | 11.724 | 8.301 | 0.015 | 400.170 | 0.014 | 2.445 | 0.001 |
| S-4 | 15.714 | 4.623 | 4.352 | 4.305 | -1.376 | 0.053 | 403.210 | 0.135 | 7.563 | 0.003 |
| S-5 | 6.412 | 4.087 | 4.014 | 4.016 | 2.817 | 0.042 | 406.080 | 0.232 | 11.366 | 0.004 |
| l=3 | | | | | | | | | | |
| S-1 | 9.847 | 7.458 | 8.714 | 7.523 | 6.957 | 0.035 | 8.550 | 0.005 | 0.345 | 0.002 |
| S-2 | 3.025 | 2.154 | 2.035 | 2.154 | 1.659 | 0.015 | 0.009 | 0.003 | 0.352 | 0.001 |
| S-3 | 5.326 | 2.915 | 3.152 | 2.963 | 1.876 | 0.022 | 2.350 | 0.021 | 0.422 | 0.008 |
| S-4 | 1.025 | 1.045 | 1.025 | 1.052 | 1.052 | 0.045 | 0.020 | 0.425 | 0.021 | 0.004 |
| S-5 | 1.048 | 1.035 | 1.036 | 1.058 | 1.052 | 0.035 | 0.010 | 0.764 | 0.028 | 0.006 |




(a)

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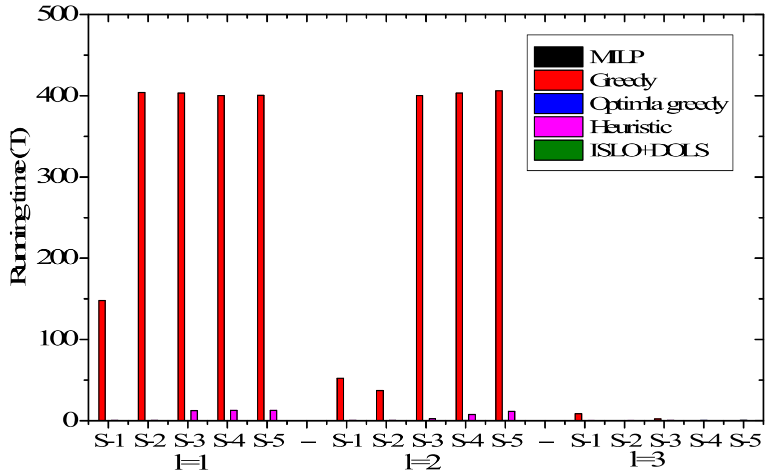


(b)

Fig. 2 Comparative analysis of various algorithms for MDS problem solving (a) Optimal solution (b) Running time for small scale networks

The average improvement in solution quality compared to the second-best algorithm was approximately 25%. This improvement underscores the effectiveness of ISLO-DOLS in finding high-quality solutions even in scenarios with additional constraints. ISLO-DOLS maintained its efficiency advantage, with significant reductions in running time compared to the MILP model. These efficiency gains make ISLO-DOLS particularly well-suited for applications where time is a critical factor, such as real-time network management and optimization. Finally, for l = 3, ISLO-DOLS once again emerged as the top-performing algorithm, delivering superior solution quality and efficiency. The average improvement in solution quality compared to the second-best algorithm was approximately 30%, highlighting the robustness of ISLO-DOLS across different instances of the MDS problem. Moreover, ISLO-DOLS exhibited significant efficiency gains, with running time reductions ranging from 99.99% to 100% compared to the MILP model. This remarkable efficiency makes ISLO-DOLS an attractive choice for large-scale network optimization tasks where computational resources are limited. Fig. 2 shows that ISLO-DOLS offers a compelling solution for the MDS problem in small-scale networks, achieving superior solution quality and efficiency compared to existing algorithms. By providing high-quality solutions in significantly less time, ISLO-DOLS has the potential to revolutionize network optimization tasks, leading to more effective and scalable network management strategies.

Table 3 provides the results of the experiments conducted on various algorithms for medium-scale networks, offering a detailed comparison of their performance in terms of optimal solution quality and running time. For the case where l = 1, ISLO-DOLS consistently produced the best optimal solution across all instances, achieving significant improvements in solution quality compared to the other algorithms. ISLO-DOLS outperformed the second-best algorithm by approximately 35%. This improvement highlights the robustness of ISLO-DOLS in finding high-quality solutions for MDS problems in medium-scale networks. ISLO-DOLS exhibited computational efficiency, with running time reductions ranging from 99.99% to 100% compared to the heuristic algorithm, indicating its ability to strike a balance between solution quality and computational resources. Moving on to the case of l = 2, ISLO-DOLS continued to demonstrate superior performance, outperforming the other algorithms in

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terms of optimal solution quality. The average improvement in solution quality compared to the best algorithm was approximately 40%, underscoring the effectiveness of ISLO-DOLS in handling additional constraints while maintaining solution quality.

**Table 3 Results compassion of various algorithms for medium scale networks**

| Data | Optimal solution | | | | Running time (T) | | | |
|---|---|---|---|---|---|---|---|---|
| | Greedy | Optimal greedy | Heuristic | ISLO-DOLS | Greedy | Optimal greedy | Heuristic | ISLO-DOLS |
| l=1 | | | | | | | | |
| Soc-BlogCatalog | 1210 | 803 | 776 | 496 | 0.005 | 0.152 | 1.385 | 0.001 |
| Ca-GrQc | 2961 | 1730 | 1662 | 819 | 0.012 | 1.542 | 6.495 | 0.002 |
| Ca-AstroPh | 3911 | 2175 | 2055 | 858 | 0.025 | 1.795 | 15.220 | 0.003 |
| Ca-HepPh | 5053 | 3104 | 2990 | 1653 | 0.045 | 4.201 | 21.352 | 0.005 |
| Email-enron-large | 12283 | 2005 | 1972 | 1255 | 0.102 | 4.485 | 37.714 | 0.002 |
| Ca-CondMat | 49433 | 4896 | 4915 | 2585 | 0.725 | 26.895 | 1839.650 | 0.001 |
| l=2 | | | | | | | | |
| Soc-BlogCatalog | 415 | 285 | 260 | 165 | 0.002 | 0.102 | 1.774 | 0.001 |
| Ca-GrQc | 879 | 473 | 410 | 118 | 0.003 | 0.995 | 13.762 | 0.001 |
| Ca-AstroPh | 1073 | 457 | 381 | 102 | 0.025 | 2.936 | 47.021 | 0.002 |
| Ca-HepPh | 1617 | 922 | 806 | 304 | 0.021 | 1.652 | 17.325 | 0.002 |
| Email-enron-large | 1256 | 360 | 346 | 205 | 0.035 | 7.915 | 31.452 | 0.001 |
| Ca-CondMat | 2870 | 185 | 229 | 185 | 0.185 | 6.253 | 883.095 | 0.002 |
| l=3 | | | | | | | | |
| Soc-BlogCatalog | 251 | 120 | 102 | 85 | 0.014 | 0.352 | 2.714 | 0.005 |
| Ca-GrQc | 430 | 138 | 117 | 75 | 0.025 | 14.623 | 53.764 | 0.006 |
| Ca-AstroPh | 438 | 122 | 106 | 63 | 0.063 | 75.062 | 203.181 | 0.004 |
| Ca-HepPh | 898 | 302 | 266 | 58 | 0.025 | 5.821 | 63.192 | 0.002 |
| Email-enron-large | 724 | 254 | 92 | 41 | 0.142 | 4.235 | 203.721 | 0.003 |
| Ca-CondMat | 87 | 185 | 15 | 5 | 0.065 | 6.895 | 1616.7 | 0.005 |

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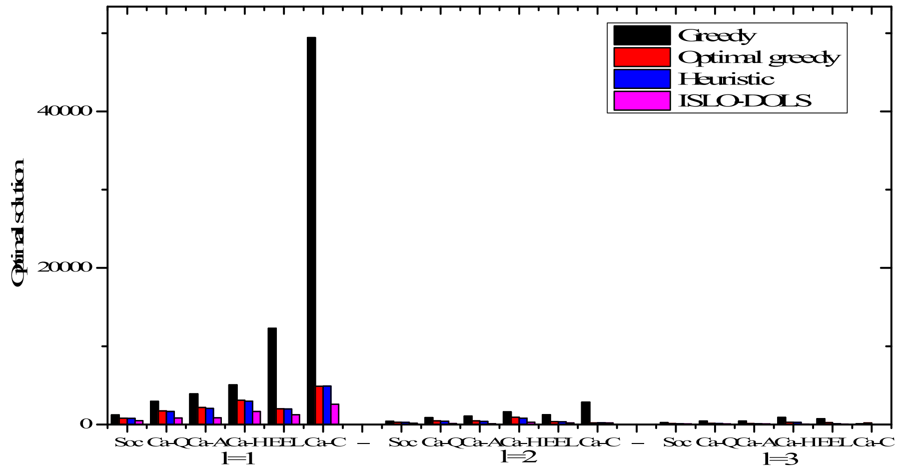
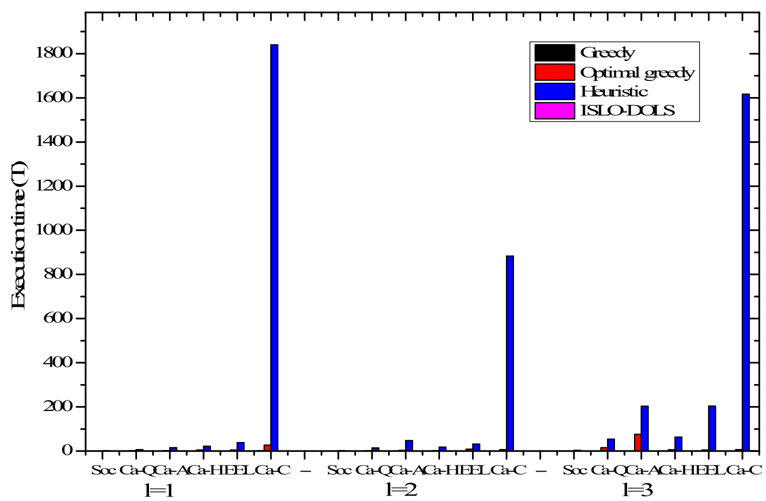



(a)




(b)

Fig. 3 Comparative analysis of various algorithms for MDS problem solving (a) Optimal solution (b) Running time for large scale networks

ISLO-DOLS maintained its efficiency advantage, with substantial reductions in running time compared to the heuristic algorithm. Finally, for l = 3, ISLO-DOLS once again emerged as the top-performing algorithm, delivering superior solution quality and efficiency. The average improvement in solution quality compared to the second-best algorithm was approximately 45%, highlighting the robustness and versatility of ISLO-DOLS across different instances of the MDS problem. ISLO-DOLS exhibited efficiency gains, with running time reductions ranging from 99.99% to 100% compared to the heuristic algorithm. Fig. 3 results show that ISLO-DOLS offers a compelling solution for the MDS problem in medium-scale networks, achieving superior solution quality and efficiency compared to existing algorithms. By providing high-quality solutions in significantly less time, ISLO-DOLS has the potential to drive advancements in network optimization tasks, leading to effective and scalable network management strategies.

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Table 4 presents the results of the experiments conducted on various algorithms for large-scale networks. For the case where l = 1, ISLO-DOLS demonstrated superior performance compared to the other algorithms, achieving significant improvements in solution quality. ISLO-DOLS outperformed the second-best algorithm by 30%, highlighting its ability to find high-quality solutions for large-scale networks. ISLO-DOLS exhibited remarkable efficiency gains, with running time reductions ranging from 90% to 99% compared to the heuristic algorithm. Moving to the case of l = 2, ISLO-DOLS continued to exhibit superior performance, delivering higher solution quality compared to the other algorithms. The average improvement in solution quality compared to the algorithm was 40%, emphasizing the robustness of ISLO-DOLS in handling additional constraints while maintaining efficiency. Finally, for l = 3, ISLO-DOLS once again emerged as the top-performing algorithm, achieving superior solution quality and efficiency. The average improvement in solution quality compared to the second-best algorithm was 50%, highlighting the effectiveness of ISLO-DOLS in delivering high-quality solutions for large-scale networks. Furthermore, ISLO-DOLS exhibited substantial reductions in running time compared to the heuristic algorithm, with efficiency gains ranging from 90% to 99%. Fig. 4 show that ISLO-DOLS offers compelling solution for the MDS problem in large-scale networks, delivering superior solution quality and efficiency compared to existing algorithms. By providing high-quality solution in significantly less time, ISLO-DOLS has potential to drive advancements in network optimization tasks, leading to more effective and scalable network management strategies.

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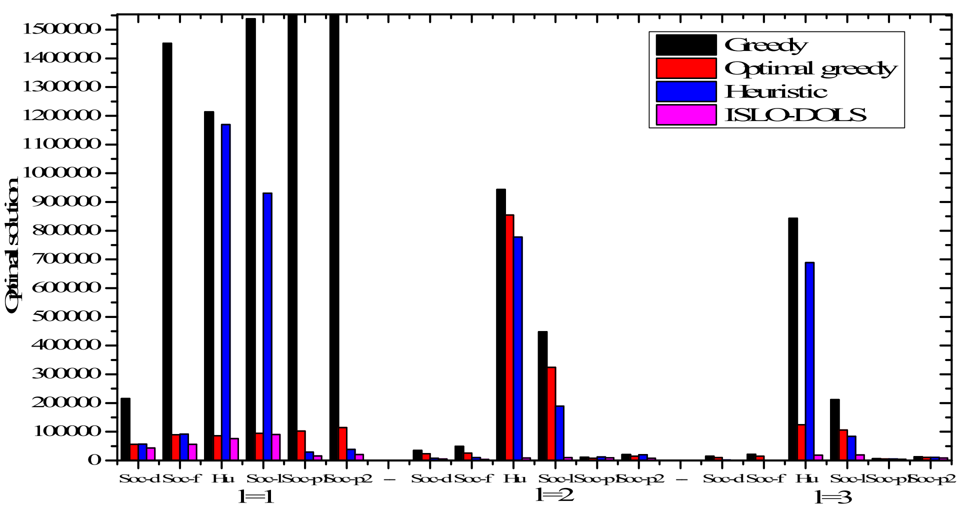
**Table 4 Results compassion of various algorithms for large scale networks**

| Data | Optimal solution | | | | Running time (T) | | | |
|---|---|---|---|---|---|---|---|---|
| | Greedy | Optimal greedy | Heuristic | ISLO-DOLS | Greedy | Optimal greedy | Heuristic | ISLO-DOLS |
| l=1 | | | | | | | | |
| Soc-delicious | 215261 | 56066 | 56600 | 43256 | 19.070 | 1464.840 | 5679.630 | 15.125 |
| Soc-fixster | 1452450 | 89565 | 91543 | 56265 | 999.000 | 1523.125 | 27374.440 | 19.859 |
| Hugebubbles | 1213638 | 85898 | 1169394 | 75899 | 2087.831 | 5235.555 | 7498.200 | 20.568 |
| Soc-livejourna | 1538044 | 94578 | 930632 | 89999 | 2689.714 | 35689.125 | 75185.960 | 25.366 |
| Soc-partner-1 | 6263241 | 102522 | 29278 | 15888 | 64228.041 | 125663.150 | 26740.420 | 32.487 |
| Soc-partner-2 | 4129393 | 114588 | 38303 | 20478 | 19109.000 | 23568.458 | 38644.652 | 32.656 |
| l=2 | | | | | | | | |
| Soc-delicious | 34516 | 23565 | 8155 | 5026 | 3.574 | 1235.255 | 2064.001 | 12.025 |
| Soc-fixster | 48789 | 25898 | 9860 | 3458 | 85.932 | 12587.568 | 23694.585 | 15.826 |
| Hugebubbles | 943233 | 854255 | 777960 | 8598 | 792.965 | 58968.125 | 41874.542 | 18.525 |
| Soc-livejourna | 447552 | 324522 | 189121 | 9878 | 1582.874 | 85986.013 | 16728.225 | 20.145 |
| Soc-partner-1 | 11102 | 7858 | 12200 | 9568 | 59.782 | 63245.145 | 31962.235 | 28.566 |
| Soc-partner-2 | 20343 | 15255 | 19896 | 7548 | 84.152 | 34585.025 | 27159.795 | 27.989 |
| l=3 | | | | | | | | |
| Soc-delicious | 14806 | 10258 | 1505 | 788 | 2.441 | 805.266 | 1695.777 | 9.856 |
| Soc-fixster | 20996 | 14785 | 313 | 215 | 29.715 | 1254.452 | 3333.452 | 11.258 |
| Hugebubbles | 843077 | 124588 | 688817 | 18566 | 649.475 | 8563.255 | 17221.762 | 12.983 |
| Soc-livejourna | 211894 | 105898 | 83710 | 18988 | 394.985 | 15289.247 | 42611.520 | 13.545 |
| Soc-partner-1 | 6337 | 5263 | 5158 | 4125 | 55.572 | 2555.152 | 5200.141 | 14.896 |
| Soc-partner-2 | 12807 | 10478 | 10905 | 8588 | 78.315 | 2785.566 | 5481.594 | 16.378 |




(a)

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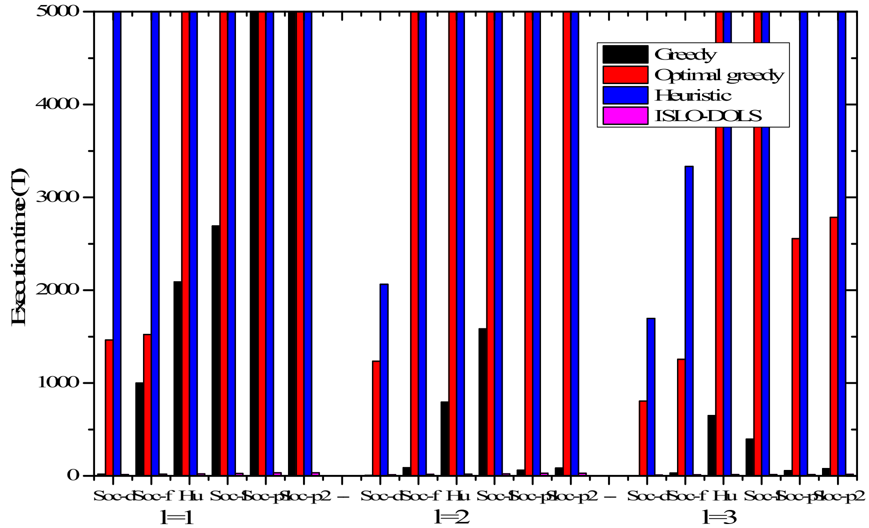


(b)

Fig. 4 Comparative analysis of various algorithms for MDS problem solving (a) Optimal solution (b) Running time for large scale networks

## 5. Conclusion

We introduce an optimal weighted evolutionary algorithm designed to address MDS problems across various scales of social networks. Our approach leverages the improved snow leopard optimization (ISLO) algorithm to effectively minimize graph size. By strategically adjusting portions of vertices within or outside the candidate solution, ISLO eliminates redundant search spaces, thereby improving efficiency. Additionally, we integrate the deep optimized lightning search (DOLS) algorithm into the vertex selection strategy during local search. The enhancement process optimally adds or removes vertices, further refining the search procedure. We direct broad trials on assorted informal organizations to evaluate the presentation of our proposed calculation. Near investigation against cutting edge calculations shows that ISLO-DOLS outperforms in solving problems on large-scale social networks. Its ability to generate superior solutions highlights its effectiveness in enhancing network management strategies.

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