A Literature Review to Identify Research Opportunities for IP Network Optimization based on Bio Inspired Algorithm

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***Abstract*—To maintain a stable network interconnection in the Internet, IP network plays a critical role. The most common issues in IP network are unbalanced network workload and network attacks which can reduce the network performance. To mitigate such problems, network optimization can be one solution. This paper conducts a literature review to present research opportunities to solve network optimization problems in IP network using algorithms inspired by nature (referred to as bio inspired algorithm) which are widely known to solve complex human discovery problems. As a result, this paper found that only 11% of previous works that used bio inspired algorithms for network optimization such as ant colony optimization algorithm, genetic algorithm, particle swarm optimization algorithm, and fish swarm algorithm. Hence, bio-inspired-algorithm-based solutions for optimization in IP network are still promising. Improving network optimization is critical to enhance communication speed and stability over internet.**

***Index Terms*—IP network, IP network optimization, bio inspired algorithm**

I. Introduction

IP network is a platform that handles data transport over the Internet involving a lot of equipment and technologies [1]. The interaction between networks in the Internet is supported by a well-structured protocol framework which creates a secure path for data to reach its destination [1]. Furthermore, IP network is implemented as the third layer of Open System Interconnection (OSI) model. OSI model is a standard for telecommunication communication protocols, particularly to manage the interoperability among various communication systems. However, the degradation of data transmision performance over the IP network cannot be avoided and mostly is caused by following reasons:

1) The congestion caused by the large amount of data that needs to be transmitted at the same time [2]
2) Poor network quality [3]
3) Network attacks [4]

To enhance such data transmision performance over the Internet, network optimization is needed to obtain a good network service quality by minimizing the impact of congestion, poor network quality, and network attacks. In this regard, network optimization means maximizing the utilization of existing resources [5]. There are many optimization methods, and one of them can be obtained from the nature which is referred to as a bio inspired algorithm. This paper is interested in bio-inspired-algorithm-based optimization because they are widely known to solve complex human inventions problems, and according to [5], such methods are also implementable to solve network performance issues during data transmision. To find the research opportunities in network optimization using bio inspired algorithms, this paper aims to perform a literature review to help the reader finding research gaps on this topic.

The rest of this paper is structured as follows. Section 2 explains the literature review method. Section 3 presents the existing works talking about optimization methods, and Section 4 analyzes current works related to bio-inspired-algorithm-based network optimization. Finally, we drawn conclusions in Section 5.

II. Bio Inspired Algorithm

Bio inspired algorithm is a computational method for optimization which learns and imitates the behavior of creatures living in the nature [6]. This algorithm can also be considered as a heuristic-based advanced method called meta-heuristic [7]. Different from analytical solution methods, bio inspired algorithms do not emphasize on proving whether a solution is correct, but they focus on computation performance, efficiency, and simplicity [6].

As a meta-heuristic, bio-inspired-algorithm is based on a deterministic theory which philosophically believes that all occurences are triggered by the external causals, and, therefore, they are the inevitable stochastic process of the nature. The stochastic process is one way of quantifying the relationships among a set of random events. Hence, the basis of bio-inspired-algorithm for optimization problem solving is population behavior iteration using randomization [8].

Currently, bio inspired algorithms are used in many applications such as electric power, security, control, and telecommunications. Its ability to decrypt and to resolve complex relationships from simple conditions using less of knowledge of the search space is the main advantages of bio inspired algorithms. The taxonomy of bio-inspired-algorithm can be grouped into three categories: 1) Evolutionary algorithm, 2) Swarm intelligence algorithm, 3) Ecological inspired algorithm. These categories will be presented in the following sub-section.

A. Evolutionary Algorithm (EA)

Evolutionary algorithm (EA) is inspired by the evolution of creatures in nature. EA has been widely used to solve various scientific specialties in real-time applications to find optimal solutions of complex optimization problems [9]. EA has three sub-categories namely Genetic algorithms (GA), Genetic programming (GP), and Evolutionary Strategy (ES) [8].

B. Ecological Inspired Algorithm (EIA)

Ecological Inspired Algorithm (EIA) is conceptually based on the natural balance in the ecosystem comprising air, land, water, and creatures which compete and cooperate to each other. The interactions between components in such ecosystem are divided into three groups based on their characteristics, namely mutualism, parasitism, and commensalism [10]. EIA has two sub-categories of algorithms [11]:

- Temperature sex dependent (TSD) which is used to determine the gender of an embryo/larval based on their temperature during cultivation [12]
- Biogeography-Based Optimization (BBO) which is inspired by the mathematical model of biogeography that consists of two variables: migration and habitat mutation. This mathematical model was proposed by R. McArthur and Edward W, who investigated the distribution of species in nature over time and space [13].

C. Swarm Intelligence Algorithm (SIA)

Swarm Intelligence algorithm (SIA) is designed based on the ability to achieve the goals of intelligent agents which have good organizational and cooperation skills such as ants, fish, and birds. [14] introduced such algorithms in 1989 as an optimization model for controlling robots. The example algorithms in this category are as follows:

- ACO (Ant Colony Optimization) algorithm which is inspired by the ants' behavior in finding the shortest path between their current location and food sources by communicating to each other through smelly chemicals called pheromone [15].
- Particle Swarm Optimization (PSO) which is inspired by the behavior of ranger bird while foraging for food. Conceptually, the swarm of birds will follow an individual bird, referred to as a particel, in the foraging area. This particel will set up the flying speed in the foraging area, and its position will be considered as the best position. Other birds, then, will adapt with particel's speed and position [16]. PSO has been widely used in many areas of optimization involving tracking process, and it has an efficient computational feature, easy implementation, and high reliability.
- Elephant Herding Optimization (EHO) algorithm is a searching method based on herd metaheuristic to solve optimization problems, and inspired by the behavior of elephants in nature to herd their groups [17].
- Artificial Bee Colony (ABC) algorithm is a swarm-based meta-heuristic algorithm and inspired by the intelligent behavior of honeybees in foraging their food by marking identified rich food sources as a positive feedback and leaving the poor ones as a negative feedback [18].
- Fish Swarm Algorithm (FSA) duplicates the behavior of an intelligent fish such as searching, swarming, and following. The effectiveness of the FSA is influenced by two factors, namely visual and step [19].
- BFO (Bacterial Foraging Optimization) algorithm is based on the characteristic of ecoli bacteria to find food [20]
- Firefly Algorithm (FA) algorithm is a swarm-based heuristic inspired by the blinking behavior of fireflies for limited optimization purposes [21]
- Glowworm Swarm Optimization (GSO) algorithm is inspired by the behavior of fluorescent worms whose movements are based on the distance between them, and the light intensity of their bodies called luciferin [22].
- Bat Algorithm (BA) algorithm is based on metaheuristic and inspired by bat's behavior responsing loudness levels of sounds [23].

III. Research Method

The method in our research is illustrated in Fig. 1. First, we select some journal indexing providers such as Science Direct, Scopus, Springer link, Clinical Key, Pro quest, and Google Scholar. After that, two types of queries are sent to the journal indexing providers using different related keywords. For example, the first query will use keywords such as "IP optimization", "bio inspired algorithms", and etc. The second keywords are the combination between the algorithm terms and the term "IP". For example, "ant colonization optimization" "IP", "Particle swarm" "IP", "genetic algorithm" "IP, and "fish swarm algorithm" "IP". The results of the two queries are filtered by publication year (e.g. 2016 to 2021). When the journals/articles obtained from the first query are matched with ones from the second query, these journals will be used for literature review.

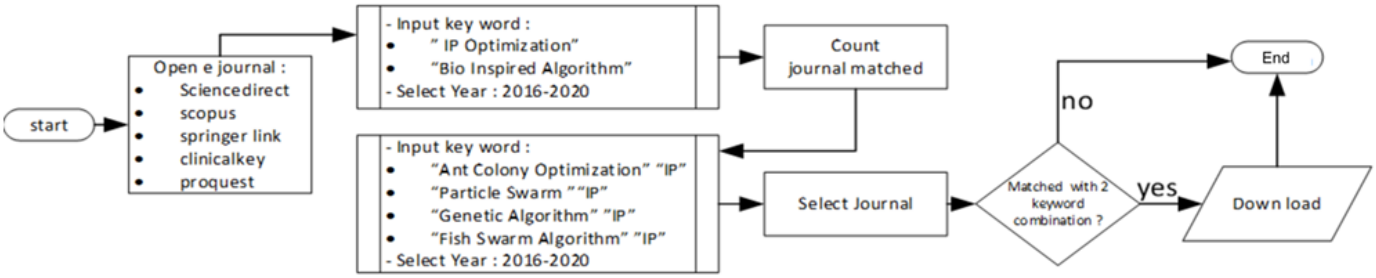


Fig. 1: Flowchart of literature searching for review

IV. RESULTS AND DISCUSSION

Fig. 2 and Fig 3 show the number of papers queried using the keyword "IP Optimization" and "bio-inspired-algorithm" in several journal indexing providers in the period of 2016 - 2020, respectively. These numbers indicate that the genre of IP optimization and bio-inspired-algorithm are interesting research areas.

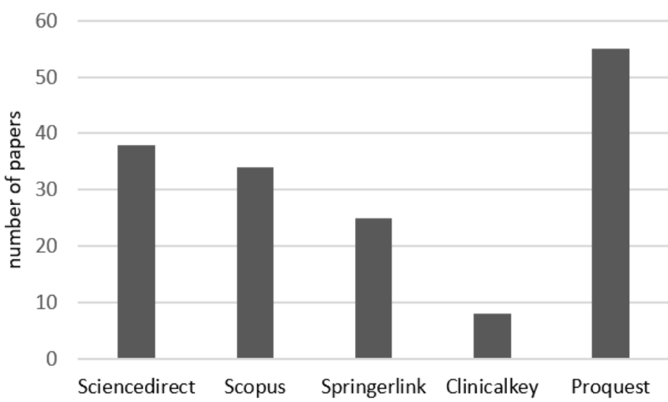


Fig. 2: Comparison of searching result using keyword IP Optimization

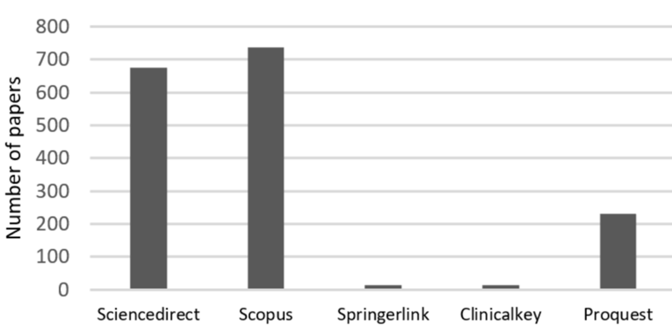


Fig. 3: Comparison of searching result using keyword Bio Inspired Algorithm

Furthermore, after we narrowed down the results by comparing IP network optimization cases using bio inspired algorithms to other algorithms, we found that only 11% of studies taking advantage of bio inspired algorithm capabilities to solve their problems (see Fig. 4). From the 11%, Fig. 5 and Fig. 6 shows the number of papers discussing IP network optimization using *genetic algorithm*, *ant colony optimization*, *particle swarm pptimization*, and *fish swarm algorithm*. In this regard, we only selected Scopus and Sciencedirect as the most trustworthy indexing journal system to find out convincing journals in IP network optimization areas.

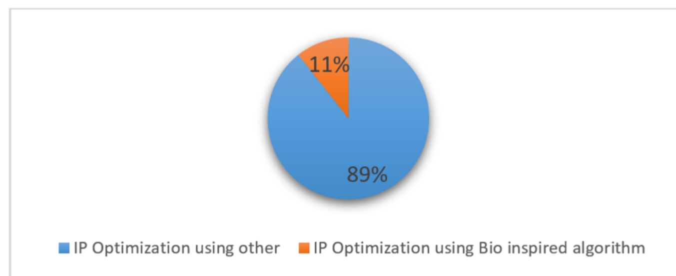


Fig. 4: The percentage of papers implementing bio-inspired-algorithm for IP Network Optimization

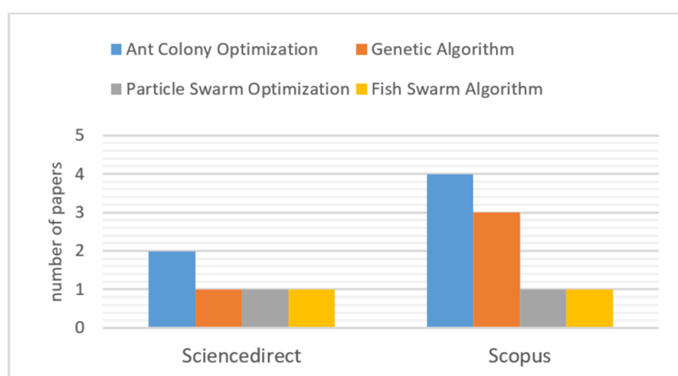
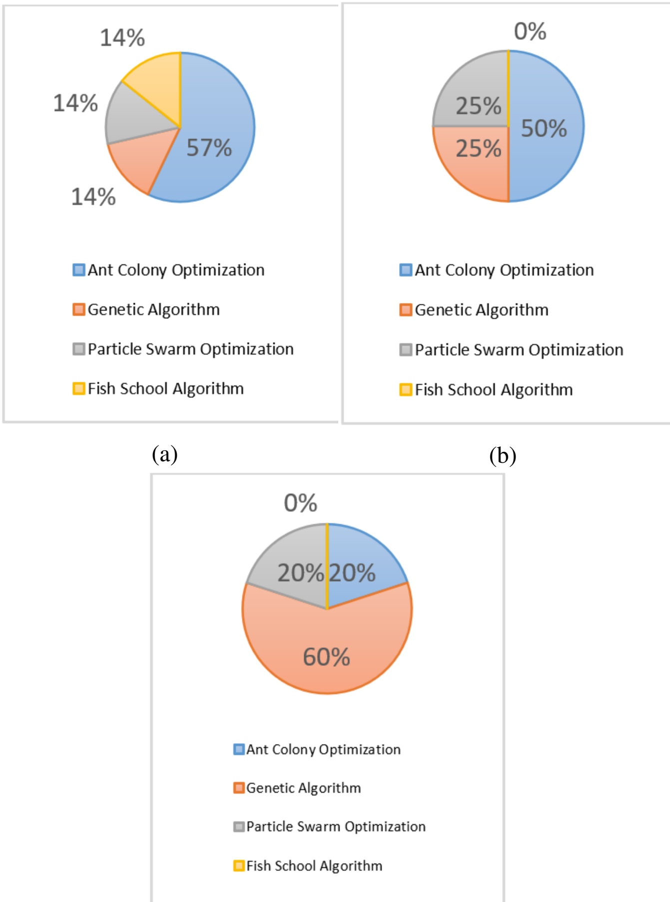


Fig. 5: The number of papers talking specific sub-categories of bio inspired algorithms used for IP network cases

By focussing on the findings illustrated in Fig. 5 and Fig. 6, the following sub-sections will discuss four bio inspired algorithms for IP network optimization cases comprising *genetic algorithm*, *ant colony optimization algorithm*, *particle swarm optimization algorithm*, and *fish swarm algorithm*.



(c)

Fig. 6: Comparison Number of Papers of Research Published based on Bio Inspired Algorithm (a). IP optimization, (b). Anomaly detection of IP network optimization, (c). Capacity management IP network optimization

A. *IP Network Optimization using Genetic Algorithm*

In genetic algorithms, genetic representation needs to be defined as it serves two purposes: as a sign of tasks completion and to provide evaluation functions. In this regard, the default genetic representation is a series of bits sent through the network. The benefits of using genetic representation are its precisions and manageable as it has a fixed size which makes cross operation simple.

Genetic algorithms can be formulated into several steps [9] as follows:

1) Forming a population of individuals with random circumstances
2) Evaluating the suitability of each individual situation with the desired results
3) Select the individual with the highest match
4) Reproducing and conducting examinations between selected individuals interspersed with mutations
5) Repeat steps 2 - 4 until you find the individual with the desired result

An example of GA implementation in an IP network can be found in a study conducted by Renata E, et.al., in 2013. This study focused on optimizing the IP network service quality index Multi-Protocol Label Switching (MPLS), particularly to address the need to assure network data flow quality, such as minimum bandwidth or maximum delay using genetic algorithms. For this regard, the researchers used route selection in IP MPLS network by developing VN-MGA (Variable Neighborhood Multi-Objective Genetic Algorithm), which is a genetic algorithm based on NSGA-II (Non-dominated Sorting Genetic Algorithm II).

NSGA-II itslef consists of two levels of representations, namely Level 1 and Level 2, to minimize rejection on simultaneous requests and network cost, including to keep the weight of routes in the network balanced. At Level 1, the solution for network problems is encoded by considering decision variables forming routes to be followed by each request from routers. Meanwhile, Level 2 is encoded based on requests sequence. In this regard, Level 1 is kept constant.

Another example can be obtained from [24] to address problems in the application of two-levels crossover operators. At level 1 the crossover exchanges individual route codes in the genetic material. At level 2, the crossover is performed by combining individual request sequences. This way, IP optimization on service quality and traffic engineering can be implemented. Even though this literature is outdated, it is still possible to develop ideas for networks optimization from it.

B. *IP Optimization using Ant Colony Optimization (ACO)*

ACO is used to determine the probability of a route will be selected from the initial location to the destination. The probability is calculated based on the displacement factors. The algorithm of ACO can be written as follow:

$$\rho^k_{xy} = \frac{(\tau^\alpha_{xy})}{(\eta^\beta_{xy})(\tau^\alpha_{xy})(\eta^\beta_{xy})}$$

where ρ^k_{xy} is the probability of ant movements from one state x to another state y. Furthermore, τ_{xy} represents the trace level of the displacement which in the ant world is called pheromone with $\alpha \geq 0$ as the control parameter. η_{xy} represents the factor attractiveness of displacement with $\beta \geq 1$ as the parameter to control its influence.

The traces are usually updated when all ants have completed their solution. In this regard, the algorithm will increase or decrease the trace level to indicate a ”good” or ”bad” solution. The example rule for such trace level can be denoted by:

$$\tau^\alpha_{xy} \leftarrow (1-\rho)\tau^\alpha_{xy} + \sigma_k \Delta\tau^k_{xy}$$

where τ^α_{xy} is the number of pheromones left on the xy trail, ρ is the pheromone evaporation coefficient, and $\Delta\tau^k_{xy}$ the number of pheromones left by the ants k. Furthermore, the cost of the ant travelling on the xy course ($\Delta\tau^k_{xy}$) is denoted as follow:

$$\Delta\tau_{xy}^{k} = \begin{cases} \frac{Q}{L_k}, & whereL_k \neq 0 \\ 0, & L_k = 0 \end{cases}$$

where Q is a constant, and L_k is the cost of the ant tour k (usually length) [15]. If $L_k = 0$, $\Delta\tau_{xy}^{k}$ equals to 0.

Wang Ping, et al, in 2016 conducted research to deal with malware attacks on IP lines by identifying the origin of the attack using IP traceback (IPTBK) which implements the Ant colony optimization algorithm. This method identifies the most likely attack paths with the limitation on the number of routing packets required (i.e., cost) and convergence time.

IPTBK solution uses two nodes randomly selected from V_s and V_d as the suspected attack source and suspected attack target, respectively. ACO is used to determine the most likely route of attack between V_s and V_d. Additionally, the Waxman model is used as a random graph generator to create a network topology. The random generator assigns the total p nodes as an integer value to mark coordinates distributed over an $n \times n$ rectangular area. The weight of each edge connecting adjacent nodes in the network topology is calculated using the Eucludian distance. This way, the maximum distance between two nodes can be generated as well. Furthermore, a method called Monte Carlo is used to generate routing information by placing m ants at random initial nodes in the topology for random attack simulations. Such information is used to reconstruct the attack path where each ant builds a tour by repeatedly following the migration rules [25].

From IPTBK cases, we can infer that the ACO algorithm is very suitable for IP optimization in routing aspects. However, developing attack simulation will be difficult if the network is large and complex.

C. IP Optimization using Particle Swarm Optimization (PSO)

The PSO algorithm, can be written as follows:

$$V_i(t) = V_i(t-1) + \varphi_1.r_1.[X_{blp} - X_i(t-1)] \\ +\varphi_2.\ r_2.[X_{bgp} - X_i(t-1)]$$

and

$$X_i(t) = X_i(t-1) + V_i(t)$$

where $V_i(t)$ = particle-*i* velocity, φ_1 and φ_2 are constants, r_1 and r_2 are random values normally distributed with the range of $[0, 1]$, and x_{bgp} represents best global position of the flock.

In general, the PSO equation consists of 3 main terms [16]:

- Momentum, avoiding the velocity from suddenly altered.
- Cognitive, allowing the particle to learn and track the best position as individuals
- Social, allowing particle to learn from group experiences (e.g. following behavior, see Fig. 7).

Carlos Emilio et. al. (2017) used PSO to improve the Quality of Service (QoS) from end to end on IP networks by determining IP capacity. Their method defines an IP network infrastructure represented by the graph $G = (V, E)$ where

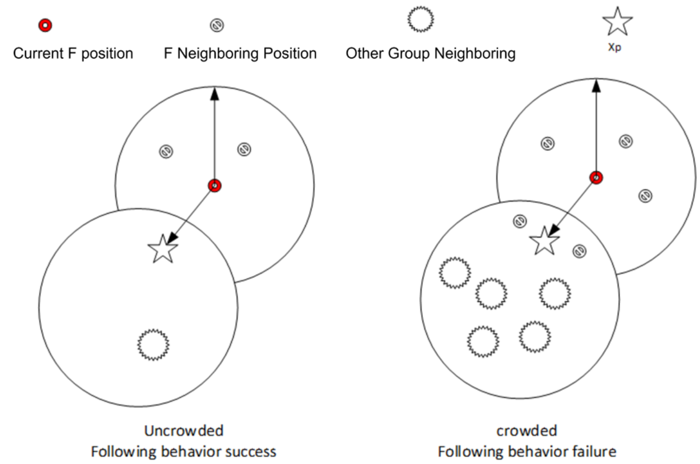


Fig. 7: Schematic diagram of the two cases when performing the following behavior

V is a set of nodes (with cardinality N) and E is a set of edges (with cardinality L). Each node represents a router in the network with a physical link connecting to its ends (other routers). Each output interface for each router is denoted by $l(i, j)$. Meanwhile, the flow $f(i, j)$ is defined as the average amount of information carried by the physical link. $C(i, j)$ represents the maximum information capacity that can be sent in units of bits per second (bps).

In PSO implementation, each variable $x_{in}(t)$ is rounded up to the nearest integer. This integer value is mapped to an element of the capacity set S. For example, the PSO algorithm has a solution with three values ranging from $x_{min} = 0$ to $x_{max} = 3$. These values, then, is set as link capacities and stored in S. Assuming that the three values of $X_i = (0.45, 2.67, 2.21)$, by rounding it up we can get $X_i = (1, 3, 3)$. If $S = 15, 20, 50$, the selected capacity is $C = (15, 50, 50)$. If the capacity $C(i, j)$ is smaller than the flow of each $f(i, j)$, then we can choose the next value for C from S. After the fitness evaluation is carried out, X_{blp} and X_{bgp} are updated and the stop criteria will be verified. If the evaluation does not satisfies the stop criteria, then the iteration will be repeated [26].

Optimization on IP networks is intended to provide the best service to send data packets. Data packets can be classified according to packet length, transmission delay constraints, average path length, and transmission speed. The relationship between traffic, capacity and queue delay is not expressed in closed form, but in a specific queue to model each router in the network topology.

PSO is more suitable for optimization of performance solutions with continuous variables such as determining the bit rate of the IP line or in traffic engineering when the traffic load trend is predicted to have a significant change.

D. IP Optimization using Fish Swarm Algorithm (FSA)

In FSA, the individual Fish (F) is often referred to as an Artificial Fish (AF). The mathematical equations of AF is based on random movement behavior which can be considered as the simplest behavior of AF. The movements depend on the interval value $[0, 1]$, random unit vector, and step denoted as follows:

$$X_{i_{next}} = X_i + rnd.Step.e$$

where $X_{i_{next}}$ represents the next location and X_i represents current locations. Furthermore, rnd and $Step$ indicate a random value from the interval $[0, 1]$ and the movement size (e.g. in distance unit), respectively. Then, e represents a random unit vector. The formula above describes the process of an individual fish in a group of fish while moving to $X_{i_{next}}$ from X_i with a random step size.

Foraging behavior can be considered as a type of AF behavior exploring neighboring areas through several randomized trials. When AF is foraging, it locates $Xtrial$ based on its visual limitation and moves towards $Trial_x$. If $f(trial_x) < f(x_i)$, AF will keep trying and will stop if $f(trial_x)f(x_i)$. This effort is limited by a variable called try_number during an foraging instance. If AF cannot get a good position after try_number, then AF's foraging behavior can be considered as failed.

The key of using the FSA in optimization is to code the candidate solution as AF. In 2019, Liu, Qing et. al. explored IP optimization in the multicast routing tree (MRT) to avoid congestion on IP links using FSA. In their paper, the optimization of the existing MRT in the IP network is represented by $|V|$ nodes in graph G. Hence, the candidate solution is not the existing *k* MRT, but different *k* subgraphs in G, so that AF is encoded as the $k|V|$ matrix as follow:

$$\begin{bmatrix} SubG_i \\ SubG_j \\ SubG_k \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,i} & x_{1,|V|} \\ x_{j,1} & x_{j,i} & x_{j,|V|} \\ x_{k,1} & x_{k,i} & x_{k,|V|} \end{bmatrix}$$

If $x_{(j,i)}$ = 1, the vertex *i* is a subgraph of $SubG_j$. Otherwise, it is not a subgraph of $SubG_j$. All elements associated with the source and destination in each $SubG_j$ must always be set to 1. This because the potential subgraph is tied to the source and destination interconnections. The coding scheme for such a problem can be described with a simple example, as follows: Assuming that there are two multicast sessions on the IP network represented by two potensial subgraphs SubG1 and SubG2 in coding scheme (illustrated in Fig. 8). SubG1 and SubG2 can be coded as AF-*X*, where *X* represents the elements corresponding to the source and destination, and their values cannot be changed [27]. The matrix generated for this case is as follows:

$$\begin{bmatrix} SubG_1 \\ SubG_2 \end{bmatrix} = \begin{bmatrix} X & 1 & 1 & X & X & 1 & X & 1 & 0 & X \\ 0 & 1 & 0 & 1 & 1 & 1 & 0 & X & X & 1 \end{bmatrix}$$

FSA can be implemented for IP ntework optimization to estimate the weight of each nodes, node capacity, and routing. However, writing the FSA algorithm into programming codes is quite complicated because the solution is a matrix which is produced according to its purpose.

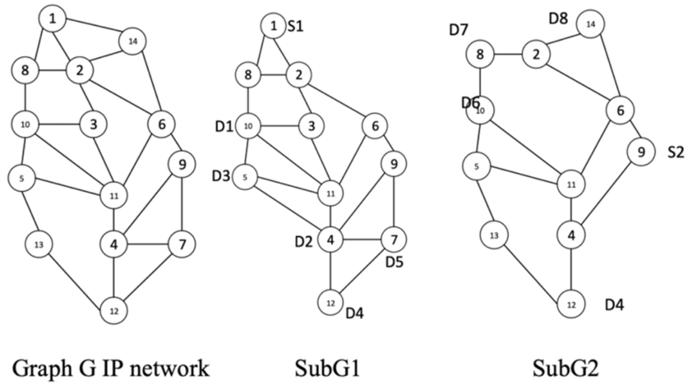


Fig. 8: Pruned tree structure

V. Conclusions

IP network is a technology which grows rapidly to a broader scope. Optimization is needed to provide a better data exchange among applications from different networks connected through the Internet. A bio-inspired-algorithm-based optimization method is one of the recommended alternatives as it can adapt with complex problems by minimizing the impact of causal factors. Research related to IP optimization with bio inspired algorithms to address IP network problems is still relatively small. It is only 11% of the journal list resulted from our queries on journal indexing providers which talk about IP network optimization, and half of them implements ACO method. Other IP optimization topics are related to routing optimization, anomaly detection, network attack, and capacity management. In the meantime, other topics such as traffic engineering, network topology, and flow methods, are still open for researchers to implement bio inspired algorithm, particularly GA, PSO and FSA algorithms. Moreover, GA and PSO can be used for anomaly detection in the network while ACO and PSO are suitable to address capacity network problems.

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