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Evolutionary algorithms guided by network topologies

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ABSTRACT

This paper explores the integration of network topologies into the evolutionary algorithms. By examining various network structures, including small-world, scale-free, Internet, and tree topologies, we investigate how the arrangement and connectivity of individuals influence the selection and convergence speed of the mate in the classic algorithm. The study compares traditional evolutionary approaches with those guided by specific network topologies, revealing that certain configurations can significantly improve algorithm performance. Our findings indicate that the use of diverse network architectures leads to promising improvements in the optimization process. This research contributes to understanding how network theory could optimize evolutionary computation and shows the way for future studies to explore additional network models and optimization problems.

Keywords: Evolutionary algorithms, network topologies, optimization problems
Mathematics Subject Classification (MSC): 68W50, 05C82, 05C15

Computing Classification System (CCS) Networks $\sim$ Network properties $\sim$ Network structure $\sim$ Network topology types

1 INTRODUCTION

Evolutionary algorithms (Fogel, O. and Walsh, 1998) have become influential instruments based on the ideas of genetics and natural selection. When tackling complex/NP issues where traditional/combinatorial methods would not work, these algorithms represent a heuristic approach. Some clever heuristics (Mojtaba Moattari, 2020; Eneko Osaba, 2014) and distributed computations (Eneko Osaba, 2015; Niño, 2012) have been performed in the past. The underlying structure of the population and the techniques used for selection can have an impact on how well evolutionary algorithms perform. This research hypothesizes that the arrangement and connectivity of persons inside a network can improve the efficiency and efficacy of the optimization process. Explores the integration of network topologies into the main algorithm.

Network topologies (Jiang, 2015) play a critical role in defining the spatial and relational layout of nodes and shaping the nature of interactions within a system. This study investigates the effects of different network configurations, including small-world, scale-free, internet, and tree topologies, on mate selection and algorithm performance. This study aims to shed light on the potential advantages and drawbacks of hybrid methodologies by comparing traditional evolutionary approaches with those guided by particular network topologies. The results presented herein advance not only the theoretical understanding of evolutionary algorithms.

In order to use and test the proposed variation for the evolutionary algorithms, a complex and nontrivial problem should be selected; the Graph Coloring Problem is NP-complete (Dailey, 1980) to decide if a given graph admits a k coloring for a given k except for the cases $k \in \{0, 1, 2\}$. This problem, like any other NP-problem, allows us to use evolutionary algorithms to test our proposal.

2 NETWORK TOPOLOGIES

The placement and connectivity of nodes, such as computers, switches, and routers, within a network is referred to as its topology (Jiang, 2015). They specify the logical or physical configuration of the connections and communication channels of various devices. The way data flow, network performance are maintained, and fault tolerance is achieved in a large way in network topologies. Variations in topology can have an impact on scalability, speed, and dependability. Some common topologies are bus, where all nodes are connected to a single central wire; ring, where nodes are connected in a circular pattern; and star, where all nodes are connected to a central hub. Based on particular requirements and objectives, network design decisions are influenced by the advantages and trade-offs of each topology.

The proposed model uses different network/graph topologies to guide and optimize an evolutionary algorithm. The selected network topologies and the justification for the selection are presented below.

2.1 Complex networks topology

A complex network is a graph with nontrivial topological properties studied in network theory. These networks are named "complex" because their behavior and structure cannot be easily understood by examining individual components; instead, they must be studied in terms of the whole system.

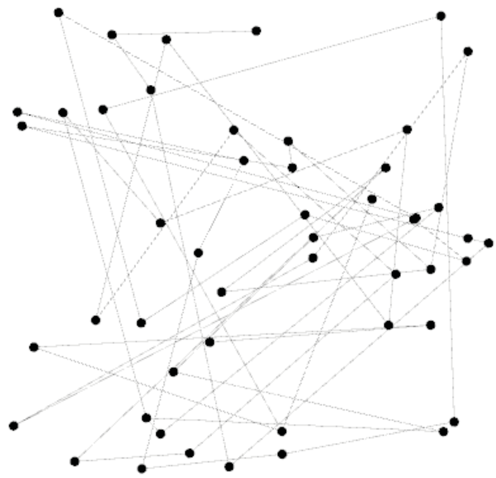

Figure 1: Small world network example using networkx (*Networkx*, n.d.) and displayed using Gephi (*Gephi*, n.d.)

Complex networks have previously been applied to enhance evolutionary algorithms. Mainly focus on small-world networks (Madrid, Guerrero and Banos, 2020; Triana, Bucheli and Garcia, 2020; Triana, Bucheli and Solarte, 2022) but also research on scale-free networks (Llanos, Muriel, Triana and Bucheli, 2022) and Erds-Rényi (Bucheli, Solarte and Ordoñez, 2024). Other similar studies on other optimization algorithms, such as the whale optimization Algorithm (WAO), have been made (Triana, Delgado and Martinez, 2023).

2.2 Tree topology

A tree topology is a hierarchical structure with a root node and multiple tiers of child nodes arranged in a tree-like fashion. It combines the best features of bus and star topologies, facilitating hierarchical data administration and simple extension chat(Jiang, 2015).

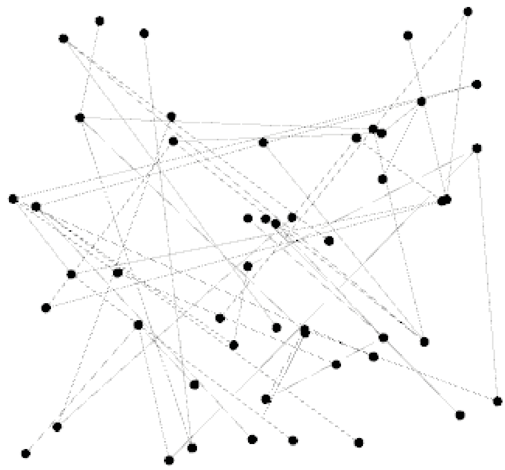

Figure 2: Tree generated using networkx and displayed using Gephi

Tree topology has been applied to optimize optimization algorithms (Bijur, Ramakrishna and Kotegar, 2021; Rokach, 2005), making this kind of graph architecture a good candidate for this research.

2.3 Internet topology

The internet graph network, also known as the internet graph in short, is a graph theory model that depicts the interconnectedness and organization of the Internet (Motamedi, Rejaie and Willinger, 2015). This type of graph/network has scale-free networks (Broido and Clauset, 2019), and recent research shows promising results in optimization algorithms (Llanos et al., 2022), making this graph topology a good candidate.

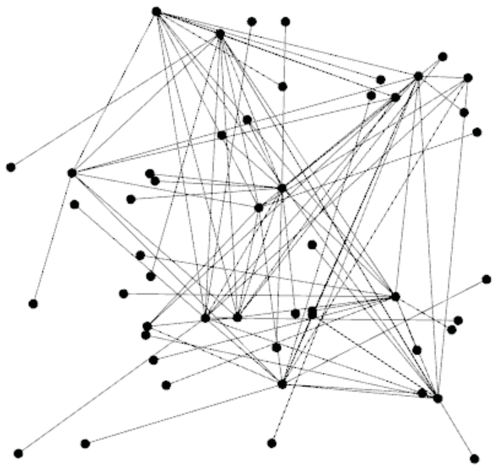

Figure 3: Internet network generated using networkx and displayed using Gephi

3 GRAPH COLORING PROBLEM

The primary purpose of graph coloring is to assign labels, called "colors," to elements of a graph with a set of given constraints. It is a way to color the vertices of a graph so that no two adjacent vertices are of the same color (Marie de Lima and Carmo, 2018).

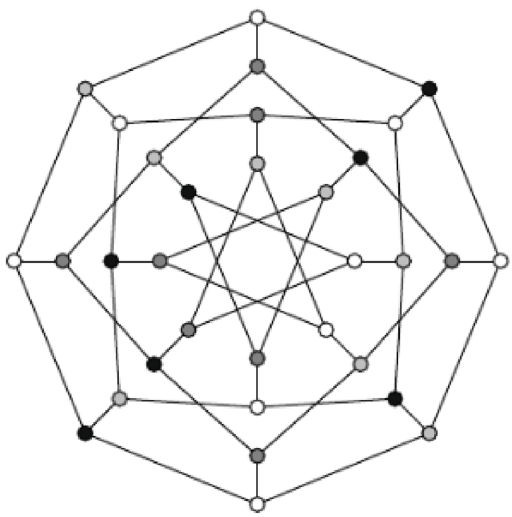

Figure 4: Graph coloring example (Formanowicz and Tanaś, 2012)

3.1 Mathematical model

The Graph Coloring Problem can be addressed as an integer linear programming model (ILP) (Marie de Lima and Carmo, 2018).

Data:

- C: Colors
- N: Nodes
- E: Edges

There are two sets of decision variables in this problem:

$$x_{i,c} \quad \text{Binary variables expressing the color of node i in c} \tag{3.1}$$

$$y_c \quad \text{Binary variables that show the usage of color C.} \tag{3.2}$$

Some restrictions must be guaranteed, such as that each node needs to have a color and that each color is being used if any nodes from one edge have a color assigned to them. Each edge can have a maximum of 1 node colored with a specific color. Ultimately, we want to reduce the total number of colors used, which is equal to y as follows:

$$Min \sum_{c \in C}^{len(C)} y_c \tag{3.3}$$

$$s.t \sum_{c \in C}^{len(C)} x_{i,c} = 1 \tag{3.4}$$

$$x_{i,c} - x_{j,c} <= y_c \;\; \forall i, j \in E, c \in C \tag{3.5}$$

$$yc_{k-1} <= yc_k \;\; \forall k \in (2, ..., |C|) \tag{3.6}$$

$$x_{i,c} \in 0, 1 \;\; \forall i \in N, c \in C \tag{3.7}$$

$$y_c \in 0, 1 \;\; \forall c \in C \tag{3.8}$$

3.2 Heuristic approach

A heuristic approach using evolutionary algorithms has been implemented for the graph coloring problem before (Islam and Pramanik, 2013; Galinier and Hao, 1999; Widi Astuti, 2015). In this proposed approach, a candidate from a population expresses color assignments for the graph vertices. These solutions are assessed based on a fitness function that gauges how well the coloring satisfies the requirement of decreasing the number of colors while guaranteeing that no two neighboring vertices share the same color. The population of solutions has evolved over several generations by applying evolutionary operators, including cross-over, mutation, and selection. Crossover combines elements of several solutions to create new ones, mutation introduces random modifications to explore different regions of the solution space, and selection promotes better performing colorings.

Algorithm 1 Pseudocode of proposed method of evolutionary computation for solving the Graph Coloring Problem

Population $\leftarrow$ pseudo randomly generated population of size n
Best_fitness $\leftarrow$ of population is selected
gen $\leftarrow$ 0
while $best\_fitness \neq 0 \; and \; gen \neq 10000$ **do**
    gen $\leftarrow$ gen + 1
    A group of population is selected $\leftarrow$ using a roulette wheel selection
    An empty new_population list is created $\leftarrow$ to save the new population
    for $i \leftarrow 1$ to n **do**
        CandidateA $\leftarrow$ i agent of population
        Child1,Child2 $\leftarrow$ are created by using a classic crossover method with CandidateA and another candidate of the population
        Child1,Child2 $\leftarrow$ are added to the the new_population list
    end for
    for $i \leftarrow 1$ to new_population.length **do**
        Mutate new_population $\leftarrow$ with a given probability
    end for
    for $i \leftarrow 1$ to new_population.length **do**
        CandidateA $\leftarrow$ i agent of population
        Get CandidateA fitness $\leftarrow$ i agent of population
        if CandidateA fitness $<$ Best_fitness **then**:
            Best_fitness $\leftarrow$ Get CandidateA fitness
        end if
    end for
end while

In this research, we want to guide the mate's selection during the crossover step in the evolutionary algorithm. Complex networks have been used to guide this selection process (Madrid et al., 2020; Triana et al., 2020; Triana et al., 2022; Triana et al., 2023; Llanos et al., 2022), we want to include and analyze other network/graph typologies such as the Internet and tree networks.

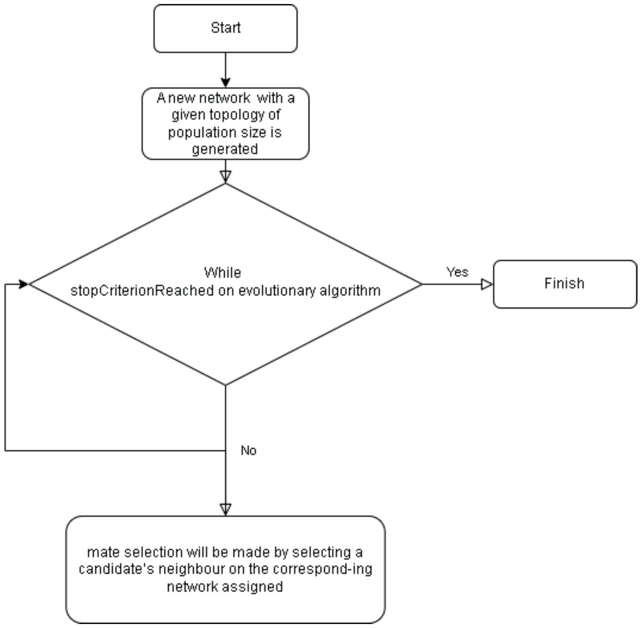

Figure 5: Mate's selection guided by an adjacent network

The code is located in this repository:
`https://github.com/jodatm/network_topologies_ea/tree/main`

4 RESULTS

The relevant parameters for the experiments are:

- Population size: 200
- Each candidate graph size: 40
- Number of colors: 25/30

In each experiment, 200 iterations were made. The results are the averages of the best candidates found in 200 experiments in each iteration. The classic/average evolutionary algorithm and the proposed model using small world, internet, and tree networks are being compared.

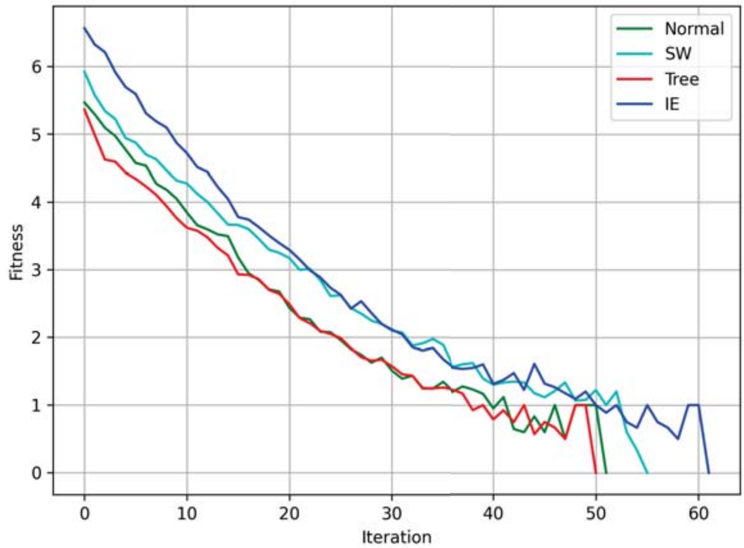

Figure 6: Fitness model fitness comparison by using 25 colors

The best results for this optimization problem are the tree model, followed by the typical evolutionary algorithm, then the small world network, and finally, the worst model is the Internet (IE) model, as shown in Figure 6. The hierarchical structure, single root node, and parent/child relationship properties work in this minimization algorithm. A similar experiment was carried out by increasing the number of colors to 30, as shown in Figure 7, and very similar results were obtained.

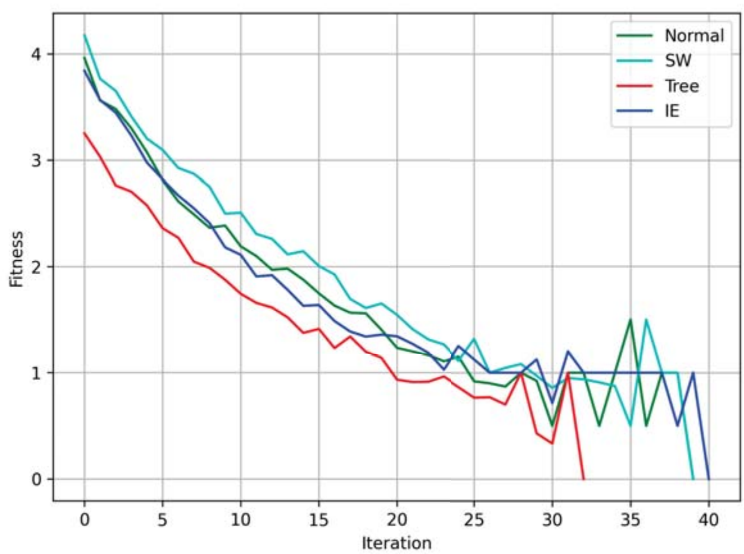

Figure 7: Fitness model fitness comparison by using 30 colors

In previous work, good results were obtained by applying selection using complex networks. However, for this particular configuration problem, it did not improve the original model. In this case, the best results were obtained with the tree model, which supports the idea that using methods from different network topologies can support evolutionary algorithms.

5 DISCUSSION AND CONCLUSION

Previous research (Madrid et al., 2020; Triana et al., 2020; Triana et al., 2022; Triana et al., 2023; Llanos et al., 2022; Bucheli et al., 2024) suggested that evolutionary algorithms guided by small-world and scale-free networks can improve the convergence speed of the optimization algorithm. The model proposed in this investigation got better results by using another kind of network topology. The present research indicates that arbitrary selection of mates between individuals using networks is not trivial and can lead to a promising enhancement to evolutionary algorithms.

The Graph Coloring Problem has been solved with different approaches before (Narayan Shukl and Garg, 2018; Douiri and Elbernoussi, 2015; Mostafaie, Modarres Khiyabani and Navimipour, 2020). Some of these or other algorithms may be better than our approach. The results obtained are promising guidance and support to the evolutionary algorithm, but cannot be said with certainty to be the best possible alternative.

Future work should focus on testing other network models, optimization problems, and algorithms to solve these problems and looking at how to support processes other than partner selection in the optimization algorithms.

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