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OPTIMIZATION OF ELASTIC OPTICAL NETWORKS THROUGH OPTIMAL ROUTING AND SPECTRUM ALLOCATION TO REDUCE COST AND INCREASE RELIABILITY

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ABSTRACT

The development of communication networks and the need for high data rate transmission led to the creation of fiber optic networks. The increasing expansion of computer networks highlighted the need to transmit a large volume of data. One of the challenges affecting elastic fiber optic networks is the optimal use of available resources. The reason is that the increased number of users disrupts network services. One way to optimize elastic fiber optic networks is to find appropriate routing for message broadcasting. Reliability and security criteria have not been discussed in the research literature. This study aims to use an efficient algorithm for routing and spectrum or frequency allocation. To enhance security and reliability, low-latency and reliable alternative paths are introduced for each node in the network so that the relevant objectives can be pursued even after the node fails. The proposed solution was evaluated on a complex problem and compared with the results of particle swarm optimization and genetic algorithms. When comparing the algorithms, criteria such as best-case convergence, average convergence, stability, and some statistical parameters were considered. The implementation conditions of all three algorithms were considered completely equal and fair. The results show the correct and appropriate performance of the global competition algorithm compared to other methods.

Keywords: Optical network optimization, routing, optimal spectrum allocation, cost reduction

INTRODUCTION

The development of communication networks and the need to send and receive high data rates led to the creation of fiber optic networks [1]. CISCO, one of the most reputable companies in the world, was founded to provide and develop network services, whose products intelligently use optical fibers. By encoding received signals into light, sending them, and then decoding them at the destination, fiber optic networks help achieve this objective. However, the further development of computer networks has raised the need for much higher data rates [2]. In some related works, the capacity of optic fibers is considered as a mesh, and each mesh acts as a communication channel [3]. In some applications, such as broadcasting, optimization algorithms are used to exploit the frequencies and capacities of the network [4].

Considering the existing parameters and challenges, the problem of improving the performance of optical networks is a non-deterministic polynomial optimization problem. As a result, the use of evolutionary algorithms is inevitable. In this research, a new evolutionary algorithm called global competition [4] is used, which has been proven to be effective. Like other optimization algorithms, this algorithm starts by creating an initial population of teams as potential solutions to the problem. Then, the teams are included in different groups and compete. The most qualified teams advance to the knockout stage. At the end of the knockout competition, the remaining team is known as the answer to the problem. The above operations are repeated until a suitable answer is obtained. The team is equivalent to the chromosome in the genetic algorithm. Subsequently, the genes are the players in the global competition algorithm. The global competition algorithm has distinct operators compared to other optimization algorithms, including shooting, crossing, passing, and attacking. Given the better performance of the global competition algorithm compared to other optimization algorithms, it is expected to have a favorable performance in the problem of increasing the efficiency and reliability of optical networks.

According to the research literature, spectrum allocation and routing in optical networks have attracted the attention of many researchers. In this section, recently published works in the field of routing and spectrum allocation are discussed. Michal et al. [5] used a tree algorithm for optimal spectrum allocation and routing. The introduced optimization method is inspired by the natural selection method using decision-making genes. In [6], researchers realized the routing and design of optical networks considering the history of sending and receiving messages. The proposed method reduced the energy consumption by 70%. However, network changes are ignored in this approach. In other words, the proposed method only considers a range of the network and ignores its changes. Also, in [7], the challenges in optical networks were studied. Most researchers have covered only one aspect of the challenges in optical networks. Therefore, determining the strengths and weaknesses of previous methods as well as their potential applications should be considered. Eavesdropping in optical networks is considered one of the security challenges and was investigated by WEI et al. [8]. They presented a model based on statistics and virtual integration of network nodes to reduce the probability of eavesdropping. According to the results of simulations, the proposed method has a good performance and increases the security in optical networks. Yanxia et al. [9] presented a model based on linear programming for spectrum allocation and routing. The proposed method is an iterative technique and the results of simulations show a significant improvement over previous method.

In previous works, routing with reliability and security has not been considered simultaneously. These two issues are analyzed simultaneously in this research. Also, improving the previous methods is another topic of interest in this research. For this purpose, the recently proposed optimization algorithm is used and tested on a network with real dimensions.

Methodology

The results of this theoretical and applied research can be used in the design of optical networks to reduce costs and increase the quality of services and routing. The library, the Internet, and reputable domestic and foreign articles have been used to collect information. The proposed method is based on the global competition optimization algorithm. Since this algorithm is originally used for discrete problems, in this research it is generalized to a continuous problem.

Problem formulation

The WCC algorithm consists of several teams, and subsequently, each team includes several players. Each team and each player are equivalent to an answer to the problem and an edge (a path), respectively. The steps of the algorithm are explained in the following section with an example. The data set includes the network nodes and the connections between them. The connections between the nodes also include information on the communication cost and reliability between the two nodes. For this purpose, two matrices are used, which are shown in Figure (1).

0	0	3	0	5
0	0	0	0	4
0	1	0	0	0
0	0	0	0	1
1	2	1	1	0

a) Communication cost

0	0	0.9	0	0.1
0	0	0	0	0.2
0	1	0	0	0
0	0	0	0	1
0.5	0.6	0.7	0.25	0

b) Reliability

Figure 1: An example of an input sample

The Hamiltonian path finding problem is an NP-hard optimization problem. In this study, a global competition algorithm is used to find the appropriate answer, the flowchart of which is represented in Figure (2).

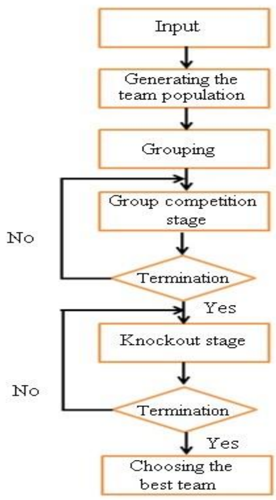

Figure 2: Flowchart of the proposed algorithm

The following describes each step of the algorithm and is formulated specifically for an optical network performance improvement problem.

Initially, the initial population of teams is received as input. Random values are used to generate the initial population. Each team is assigned random values as an answer to the problem. Therefore, the procedure starts with a set of randomly generated initial answers.

Different methods are used to group teams, such as most similar, least similar, random node, etc. In this study, the random grouping method is used to group teams. The number of teams in each group is equal. Each team is considered to have one answer to the problem. Also, grouping means creating a group of answers to the optical network performance improvement problem, which reduces to the Hamiltonian path problem.

In the group competition stage, teams compete with each other periodically. Finally, the more qualified teams advance to the knockout stage. Each team creates a copy of the opposing team and tries to improve the response state using the shooting, attacking, passing, and crossing operators. To determine the competency of the teams, a criterion must be defined. This criterion is known as the score function in the WCC algorithm. The score function in the WCC algorithm is equivalent to the fitness function in the genetic algorithm.

In the shooting operation, the current team randomly selects a series of its values and throws them toward the opposing team. If the opposing team finds a more suitable fitness or score, it records the received values. However, if its score or point value is lower than the previous value, it ignores the new values received.

In the attacking operation, each team randomly creates a series of new values and sends them to the opposing team. If the opposing team finds a more suitable fitness, it records the received values. However, if its score is lower, it ignores the new values received. Although in the shooting operation, one team sends its values to the other team, in the attacking operation, one team sends newly generated random values to the opposing team. This prevents the global competition algorithm from getting stuck in local optima.

The crossing operation randomly selects two points from a team and swaps their values with each other using the shift operator. Just like in the attacking and shooting operations, a team accepts the new values if it improves its score. Otherwise, the received values are ignored. This operator creates a new answer to the problem based on the change in the permutation of paths and fixes it as the desired result once the improvement is achieved.

In the WCC algorithm, the presence of an arbiter is required to evaluate the operations performed by the teams. The arbiter is based on the fitness calculation. The fitness or score indicates the proximity of an extended solution to an optimal solution. The scoring function plays a key role in convergence and finding the optimal solution in the optimization algorithm and is defined by experts in the field. In calculating the scoring function, the following should be considered.

Path cost: If there is a path between any two nodes of the graph, it must contain a cost. Cost is the geographical distance between the two nodes, calculated through the Euclidean relation. The cost of a path is equal to the sum of the costs between the nodes of a path, calculated through the Relation (1).

$$Total_{cost} = \sum_{i=1}^{n-1} cost(node(i), node(i+1)) \tag{1}$$

where, $Total_{cost}$ is equal to the total cost of the path. Also, the cost function is the function for calculating the cost between two nodes. As mentioned earlier, the distance between two nodes is represented by the adjacency matrix. If the algorithm generates the path 1→3→2→5→4 and the cost matrix is equivalent to matrix A in Figure (1), then the total cost of the path is equal to 9. The total cost is calculated based on the sum of the costs in the path. For example, the sum of the costs between Nodes 1 and 3 (= 3), Nodes 3 and 2 (= 1), Nodes 2 and 5 (= 4), and Nodes 5 and 4 (= 1) is equal to 9. Reliability is another criterion measured in this research. Reliability means the probability of the path being suitable for sending a message. The higher the reliability between two nodes, the lower the rate of message loss. Relation (2) is used to calculate reliability.

$$\text{Reliability} = \sum_{i=1}^{n-1} real(node(i), node(i+1)) \tag{2}$$

where *real* is the function that determines the reliability between two nodes. For example, if the algorithm has generated the previous path and the reliability matrix is equivalent to matrix B in Figure (1), then the total reliability of the path is 1/45. The total reliability is equal to the sum of the reliabilities in the path. For example, the sum of the reliability between Nodes 1 and 3 (= 0.9), Nodes 3 and 2 (=1), Nodes 2 and 5 (=0.2), and Nodes 5 and 4 (=0.25) is equal to 1.45.

In general, the scoring function is defined in Relation (3).

$$\text{Score = Normal (Reliability) - Normal } (Total_{cost}) \tag{3}$$

In Relation (3), the higher score means better fitness of a response. To equalize the effect of the two specified objectives, normalized values of reliability and cost are used. Performing the normalization operation prevents bias and achieves a correct balance between the objectives. Relation (4) is used for normalization.

$$\text{Normalization (value)} = \frac{value - \text{min}imum}{maximum - minimum} \tag{4}$$

where, *value*, *minimum*, and *maximum* represent the current value to be normalized, the lowest available value and the highest available value, respectively.

Implementation platform and input data

MATLAB version 2017 was used to implement the algorithms. All three programs were run on a system with a core i7 2.7GHZ processor and 8GB of main memory. The input, as a fully connected graph, is the same for all algorithms. The reason is to enhance the accuracy of the algorithm evaluation process. Increasing the input size and complexity of the problem better characterizes the efficiency of the algorithms. Each edge of the graph includes two criteria: distance and reliability. For this purpose, two matrices are used to represent distance and reliability. To equalize the effect of distance and reliability and prevent them from being biased, matrix normalization was used and each value was mapped to the interval 0 and 1. The normalized matrices are reflected in Figures (3) and (4).

0	0.8147	0.1270	0.6324	0.2785	0.9575	0.1576	0.9572	0.8003	0.4218	0.7922	0.6557	0.8491	0.6787	0.7431
0.8147	0	0.5853	0.7513	0.5060	0.8909	0.5472	0.1493	0.8407	0.8143	0.9293	0.1966	0.6160	0.3517	0.5853
0.1270	0.5853	0	0.1524	0.5383	0.0782	0.1067	0.0046	0.8173	0.0844	0.2599	0.4314	0.1818	0.1455	0.8693
0.6324	0.7513	0.1524	0	0.5752	0.2348	0.8212	0.0430	0.6491	0.6477	0.5470	0.7447	0.6868	0.3685	0.7802
0.2785	0.5060	0.5383	0.5752	0	0.3111	0.4302	0.9049	0.4389	0.2581	0.5949	0.6028	0.2217	0.2967	0.4242
0.9575	0.8909	0.0782	0.2348	0.3111	0	0.1068	0.4942	0.7150	0.8909	0.6987	0.0305	0.5000	0.9047	0.6177
0.1576	0.5472	0.1067	0.8212	0.4302	0.1068	0	0.0835	0.1734	0.8314	0.0605	0.5269	0.6569	0.2920	0.0155
0.9572	0.1493	0.0046	0.0430	0.9049	0.4942	0.0835	0	0.1904	0.4607	0.1564	0.6448	0.1909	0.4820	0.5895
0.8003	0.8407	0.8173	0.6491	0.4389	0.7150	0.1734	0.1904	0	0.0688	0.5309	0.4076	0.7184	0.5313	0.1056
0.4218	0.8143	0.0844	0.6477	0.2581	0.8909	0.8314	0.4607	0.0688	0	0.9160	0.4624	0.4609	0.3225	0.4714
0.7922	0.9293	0.2599	0.5470	0.5949	0.6987	0.0605	0.1564	0.5309	0.9160	0	0.4587	0.7703	0.6620	0.8419
0.6557	0.1966	0.4314	0.7447	0.6028	0.0305	0.5269	0.6448	0.4076	0.4624	0.4587	0	0.1920	0.6963	0.5254
0.8491	0.6160	0.1818	0.6868	0.2217	0.5000	0.6569	0.1909	0.7184	0.4609	0.7703	0.1920	0	0.7691	0.8085
0.6787	0.3517	0.1455	0.3685	0.2967	0.9047	0.2920	0.4820	0.5313	0.3225	0.6620	0.6963	0.7691	0	0.1476
0.7431	0.5853	0.8693	0.7802	0.4242	0.6177	0.0155	0.5895	0.1056	0.4714	0.8419	0.5254	0.8085	0.1476	0

a) The first 15 rows and columns of the matrix

0	0.1239	0.8530	0.2703	0.5650	0.4170	0.9479	0.1057	0.1665	0.5737	0.9312	0.7378	0.8604	0.9844	0.7856
0.1239	0	0.1776	0.1339	0.9391	0.2955	0.4671	0.0252	0.5590	0.3479	0.0542	0.6628	0.8985	0.9884	0.7069
0.8530	0.1776	0	0.2878	0.4648	0.8182	0.1781	0.0567	0.3358	0.2089	0.6754	0.9121	0.7455	0.5619	0.5972
0.2703	0.1339	0.2878	0	0.1341	0.8949	0.2425	0.4417	0.8972	0.0934	0.4561	0.9954	0.2973	0.2982	0.5054
0.5650	0.9391	0.4648	0.1341	0	0.6311	0.0809	0.9051	0.1092	0.3381	0.7463	0.0484	0.6035	0.7297	0.7814
0.4170	0.2955	0.8182	0.8949	0.6311	0	0.6925	0.3965	0.7802	0.6079	0.1048	0.5495	0.8905	0.7343	0.0729
0.9479	0.4671	0.1781	0.2425	0.0809	0.6925	0	0.7984	0.6837	0.7227	0.1175	0.3288	0.7491	0.7400	0.7350
0.1057	0.0252	0.0567	0.4417	0.9051	0.3965	0.7984	0	0.8669	0.3664	0.6850	0.7894	0.2060	0.7719	0.3883
0.1665	0.5590	0.3358	0.8972	0.1092	0.7802	0.6837	0.8669	0	0.2290	0.4845	0.7819	0.2941	0.5309	0.4053
0.5737	0.3479	0.2089	0.0934	0.3381	0.6079	0.7227	0.3664	0.2290	0	0.1123	0.2916	0.9644	0.6948	0.4326
0.9312	0.0542	0.6754	0.4561	0.7463	0.1048	0.1175	0.6850	0.4845	0.1123	0	0.1098	0.1875	0.7978	0.7690
0.7378	0.6628	0.9121	0.9954	0.0484	0.5495	0.3288	0.7894	0.7819	0.2916	0.1098	0	0.2729	0.6733	0.4517
0.8604	0.8985	0.7455	0.2973	0.6035	0.8905	0.7491	0.2060	0.2941	0.9644	0.1875	0.2729	0	0.0594	0.7727
0.9844	0.9884	0.5619	0.2982	0.7297	0.7343	0.7400	0.7719	0.5309	0.6948	0.7978	0.6733	0.0594	0	0.1253
0.7856	0.7069	0.5972	0.5054	0.7814	0.0729	0.7350	0.3883	0.4053	0.4326	0.7690	0.4517	0.7727	0.1253	0

b) The second 15 rows and column of the matrix

Figure 3: Normalized distance matrix

0	0.9058	0.9134	0.0975	0.5469	0.9649	0.9706	0.4854	0.1419	0.9157	0.9595	0.0357	0.9340	0.7577	0.3922
0.9058	0	0.2238	0.2551	0.6991	0.9593	0.1386	0.2575	0.2543	0.2435	0.3500	0.2511	0.4733	0.8308	0.5497
0.9134	0.2238	0	0.8258	0.9961	0.4427	0.9619	0.7749	0.8687	0.3998	0.8001	0.9106	0.2638	0.1361	0.5797
0.0975	0.2551	0.8258	0	0.0598	0.3532	0.0154	0.1690	0.7317	0.4509	0.2963	0.1890	0.1835	0.6256	0.0811
0.5469	0.6991	0.9961	0.0598	0	0.9234	0.1848	0.9797	0.1111	0.4087	0.2622	0.7112	0.1174	0.3188	0.5079
0.9649	0.9593	0.4427	0.3532	0.9234	0	0.6538	0.7791	0.9037	0.3342	0.1978	0.7441	0.4799	0.6099	0.8594
0.9706	0.1386	0.9619	0.0154	0.1848	0.6538	0	0.1332	0.3909	0.8034	0.3993	0.4168	0.6280	0.4317	0.9841
0.4854	0.2575	0.7749	0.1690	0.9797	0.7791	0.1332	0	0.3689	0.9816	0.8555	0.3763	0.4283	0.1206	0.2262
0.1419	0.2543	0.8687	0.7317	0.1111	0.9037	0.3909	0.3689	0	0.3196	0.6544	0.8200	0.9686	0.3251	0.6110
0.9157	0.2435	0.3998	0.4509	0.4087	0.3342	0.8034	0.9816	0.3196	0	0.0012	0.4243	0.7702	0.7847	0.0358
0.9595	0.3500	0.8001	0.2963	0.2622	0.1978	0.3993	0.8555	0.6544	0.0012	0	0.6619	0.3502	0.4162	0.8329
0.0357	0.2511	0.9106	0.1890	0.7112	0.7441	0.4168	0.3763	0.8200	0.4243	0.6619	0	0.1389	0.0938	0.5303
0.9340	0.4733	0.2638	0.1835	0.1174	0.4799	0.6280	0.4283	0.9686	0.7702	0.3502	0.1389	0	0.3968	0.7551
0.7577	0.8308	0.1361	0.6256	0.3188	0.6099	0.4317	0.1206	0.3251	0.7847	0.4162	0.0938	0.3968	0	0.0550
0.3922	0.5497	0.5797	0.0811	0.5079	0.8594	0.9841	0.2262	0.6110	0.0358	0.8329	0.5303	0.7551	0.0550	0

a) The first 15 rows and columns of the matrix

0	0.4904	0.8739	0.2085	0.6403	0.2060	0.0821	0.1420	0.6210	0.0521	0.7287	0.0634	0.9344	0.8589	0.5134
0.4904	0	0.3986	0.0309	0.3013	0.3329	0.6482	0.8422	0.8541	0.4460	0.1771	0.3308	0.1182	0.5400	0.9995
0.8739	0.3986	0	0.4145	0.7640	0.1002	0.3596	0.5219	0.1757	0.9052	0.4685	0.1040	0.7363	0.1842	0.2999
0.2085	0.0309	0.4145	0	0.2126	0.0715	0.0538	0.0133	0.1967	0.3074	0.1017	0.3321	0.0620	0.0464	0.7614
0.6403	0.3013	0.7640	0.2126	0	0.0899	0.7772	0.5338	0.8258	0.2940	0.0103	0.6679	0.5261	0.7073	0.2880
0.2060	0.3329	0.1002	0.0715	0.0899	0	0.5567	0.0616	0.3376	0.7413	0.1279	0.4852	0.7990	0.0513	0.0885
0.0821	0.6482	0.3596	0.0538	0.7772	0.5567	0	0.9430	0.1321	0.1104	0.6407	0.6538	0.5832	0.2348	0.9706
0.1420	0.8422	0.5219	0.0133	0.5338	0.0616	0.9430	0	0.0862	0.3692	0.5979	0.3677	0.0867	0.2057	0.5518
0.6210	0.8541	0.1757	0.1967	0.8258	0.3376	0.1321	0.0862	0	0.6419	0.1518	0.1006	0.2374	0.0915	0.1048
0.0521	0.4460	0.9052	0.3074	0.2940	0.7413	0.1104	0.3692	0.6419	0	0.7844	0.6035	0.4325	0.7581	0.6555
0.7287	0.1771	0.4685	0.1017	0.0103	0.1279	0.6407	0.5979	0.1518	0.7844	0	0.9338	0.2662	0.4876	0.3960
0.0634	0.3308	0.1040	0.3321	0.6679	0.4852	0.6538	0.3677	0.1006	0.6035	0.9338	0	0.0372	0.4296	0.6099
0.9344	0.1182	0.7363	0.0620	0.5261	0.7990	0.5832	0.0867	0.2374	0.4325	0.2662	0.0372	0	0.3158	0.6964
0.8589	0.5400	0.1842	0.0464	0.7073	0.0513	0.2348	0.2057	0.0915	0.7581	0.4876	0.4296	0.3158	0	0.1302
0.5134	0.9995	0.2999	0.7614	0.2880	0.0885	0.9706	0.5518	0.1048	0.6555	0.3960	0.6099	0.6964	0.1302	0

b) The second 15 rows and column of the matrix

Figure 4: Normalized reliability matrix

Given that the cost of the path from a node to itself is zero, the elements of the main diagonal of the matrices are zero.

RESULTS

Convergence

The convergence plot of the algorithms is shown in Figure (5). The horizontal and vertical axes indicate the generation or iteration number and the score or fitness value, respectively. As mentioned earlier, the convergence plot of the algorithms must be ascending. However, in some other problems, the minimum fitness function is considered the optimal response. This class of problems is called maximization and minimization, respectively.

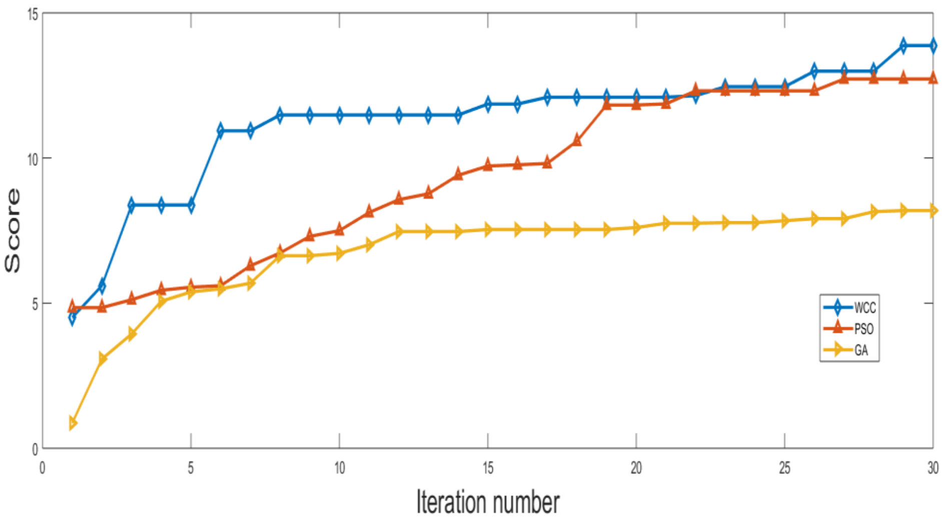

Figure 5: Algorithm convergence

The WCC, PSO, and GA algorithms are shown in blue, red, and yellow, respectively. As shown in the figure, the proposed algorithm converges faster. There is a slight improvement from the eighth to twenty-fifth generations. Although the PSO algorithm almost approaches the performance of the WCC algorithm in the eighteenth generation, it lags behind in the twentyeighth generation. Although the GA algorithm has a similar performance to the other two algorithms at the beginning of the process, it has almost stabilized after the thirteenth generation and converged at a slower rate.

Average convergence

Like the convergence plot, the average convergence plot should also be ascending. Average convergence indicates the overall evolution of the responses. According to the results, all three algorithms produced acceptable results from this point of view. Figure (6) shows the average convergence plot of the algorithms.

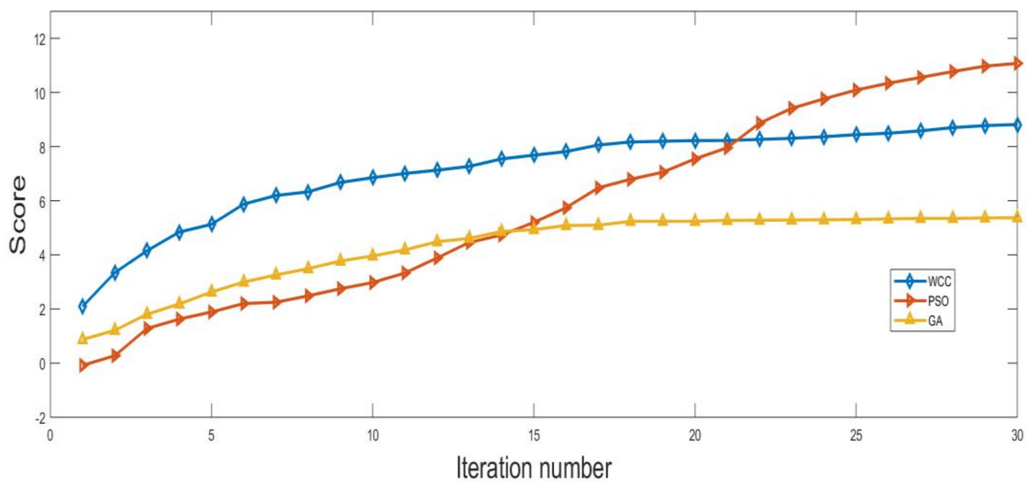

Figure 6: Average convergence

The WCC, PSO, and GA algorithms are shown in blue, red, and yellow respectively. The horizontal and vertical axes respectively indicate the number of generations or iterations and the value of the score or fitness. Although the WCC algorithm converged faster than the other algorithms, the PSO algorithm has a steeper slope in the 22nd generation and has surpassed the WCC algorithm and the GA algorithm. This shows that all particles have moved towards the best response and are stuck in the local optimum. Although the convergence of the WCC algorithm is slightly better than the GA algorithm, both algorithms exhibit almost similar behavior regarding the average convergence speed.

Algorithm stability

The stability plot of the algorithms is shown in Figure (7). The horizontal and vertical axes respectively indicate the number of executions and the score or fitness obtained at the end of the algorithm.

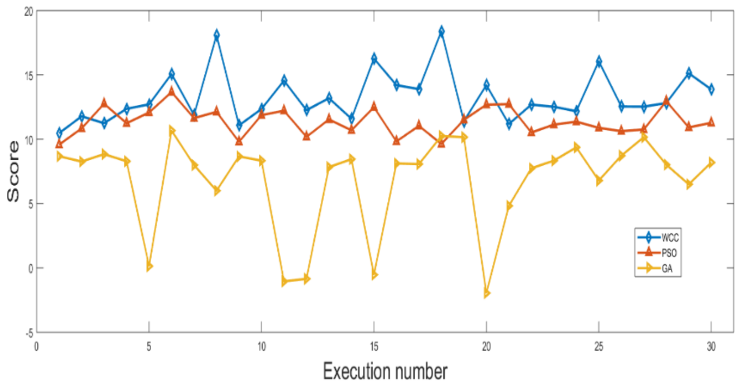

Figure 7: Stability of algorithms

As before, the WCC, PSO, and GA algorithms are shown in blue, red, and yellow respectively. According to Figure (7), the WCC algorithm is superior to the other two algorithms regarding the production of optimal results. The PSO algorithm is ranked next and is better and worse than the GA algorithm and the WCC algorithm, respectively. The GA algorithm also showed the worst performance. Regarding fluctuations and uniform behavior, the PSO algorithm had less fluctuation. After the PSO algorithm, the WCC algorithm and the GA algorithm are respectively. Although the fluctuation of the WCC algorithm is higher than the PSO algorithm, it has produced much more acceptable results.

Statistical analysis of algorithms

In this section, the algorithms are compared in terms of several statistical parameters such as:

- The standard deviation shows how far the data is from the mean. The lower the standard deviation, the better the performance achieved by the algorithm. The standard deviation is calculated based on the mean and variance values.
- The p-value indicates the probability that the generated responses were generated randomly. The lower the value of this measurement, the lower the randomness of the generated responses. According to the literature, a value greater than 0.5 indicates the random operation of the algorithms. It should also be noted that random responses are different from the random operation of the algorithms. In other words, the algorithms operate randomly, but the generated responses should not be random.
- Lowest value: This measure is equivalent to the lowest score obtained by the algorithms during different executions. The algorithm with the highest value among the lowest is more fitness.
- Highest value: This measure is equivalent to the highest score obtained by the algorithms during different executions. The algorithm with the highest value among the highest is more fitness.

Based on the different stages of execution, each algorithm requires different execution times. Naturally, the algorithm with the lowest execution time is more acceptable.

Table 1: Statistical analysis of algorithms

Algorithm	The lowest value	The highest value	Standard deviation	p-value	Execution time
WCC	11	19	1.89	2.1 E-18	3.16
PSO	9	13	1.15	1.9 E-27	4.39
GA	-2	11	3.67	5.6 E-8	2.75

Table (1) shows the results of running the algorithms in thirty consecutive runs. Each run has proceeded up to 50 iterations (generations). Also, the same number of scoring functions is called in each execution. The parameters related to the algorithms have been adjusted to achieve maximum efficiency. Regarding the standard deviation, the PSO algorithm has a stable plot with less fluctuation and naturally performs better. Although the standard deviation of the WCC algorithm is higher than that of the PSO algorithm, its results are better than those of the PSO algorithm. The GA algorithm is ranked third.

The p-value of all three algorithms is much less than 0.05. Therefore, no algorithm has reached the responses by chance. Regarding this measure, the algorithms are ranked as PSO, WCC, and GA, respectively.

Regarding the lowest value, the WCC algorithm had the best performance and its worst response score is 11. At the same time, the genetic algorithm had the worst performance with a value of -2. The worst response of the PSO algorithm is also equal to 9 and is somewhat close to the result of the WCC algorithm.

Regarding the highest value, the WCC algorithm has performed the best and its best response score is equal to 91. At the same time, the genetic algorithm has performed the worst with a value of 11. The best response of the PSO algorithm is also equal to 13 and is very far from the WCC algorithm.

The GA algorithm has obtained the best execution time. The results of all three algorithms are very close to each other. Also, the PSO algorithm has performed the worst with a time of 4.39 seconds. The difference in the execution time of the algorithms is related to the different stages of the algorithms. For example, the PSO algorithm selects the best particles in each stage, while the other two algorithms do not have this stage. Although the execution time of the WCC algorithm is very close to the GA algorithm, it has a significant advantage over the PSO.

Reasons for the superiority of the proposed method

The comparison of all three algorithms was carried out under the same and fair conditions. The algorithms were evaluated on the same system, the same input data, the same number of generations, and the same execution. Also, the same permutation concepts were used in their formulation to achieve a fair comparison. The reasons for the superiority of the WCC algorithm over other algorithms are as follows.

The operators of the global competition algorithm have a significant efficiency for permutation problems because they can produce better responses by changing the permutations appropriately. The shooting and attacking operators were changed in the implementation so that they are suitable for permutation problems.

If the operator reduces the score of the response, the changes are ignored. At the same time, other algorithms may produce a worse response than their previous state. Each of the algorithms transfers the best response of the previous generation to its current generation to improve the responses.

The group and knockout competitions in the global competition algorithm led to local and global optima, respectively. This algorithm converges faster than other algorithms with different and appropriate phases.

CONCLUSION

One of the challenges affecting elastic fiber optic networks is the optimal use of available resources. The reason is that the increased number of users disrupts network services. One way to optimize elastic fiber optic networks is to find appropriate routing for message broadcasting. This problem can be considered in the form of a node permutation problem. The problem of improving the performance of fiber optic networks reduces the problem of finding a Hamiltonian path as an NP-Hard optimization problem. To find an acceptable response to NP problems, heuristic or metaheuristic methods are used. Considering the desirable efficiency of metaheuristic methods, in this study, the efficient metaheuristic algorithm of global competition has been used. This algorithm has been generalized for the defined problem with modified operators. Also, in the definition of the scoring function, multiple criteria such as cost reduction and reliability increase in terms of a multi-objective problem are considered. A complex input was used to evaluate the proposed solution and the results were compared with the results of particle swarm optimization and genetic algorithms. In the process of comparing the algorithms, criteria such as best-case convergence, average convergence, stability, and some statistical parameters were included. The implementation conditions of all three

algorithms were considered completely equal and fair. The results show the correct and appropriate performance of the global competition algorithm compared to other methods.
It is recommended to investigate the fuzzy reliability for future work. This means that the appropriateness of the path reliability should be determined. Some of the challenges raised can be answered using fuzzification. Also, the proposed solution can be generalized to other networks such as ad hoc networks and the efficiency of the algorithms can be examined.

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