Modified GA with Adaptive Crossover and Mutation for RWA in Large-Scale Optical Backbone Networks

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***Abstract*—The Routing and Wavelength Assignment (RWA) is a fundamental challenge in wavelength-routed all-optical networks, directly impacting network cost, resource utilization, and blocking probability. For a given network topology, RWA seeks to identify optimal lightpaths and assign wavelengths such that no two connections sharing a link use the same wavelength. Due to its NP-complete nature, exact solutions are impractical for large-scale networks, motivating the use of metaheuristic approaches. This work proposes a Genetic Algorithm (GA) based RWA solution incorporating node-connectivity-aware crossover and mutation strategies. A novel tournament selection method is introduced, combining tournament scores with the fitness function to achieve an effective balance between exploration and exploitation. The objective function simultaneously minimizes wavelength usage and the number of hops per lightpath, thereby reducing overall blocking probability. Simulation results demonstrate that the proposed GA approach outperforms conventional GA methods, achieving improved resource efficiency and reduced blocking in diverse network scenarios.**

***Index terms*—Optical network, routing and wavelength assignment, continuity constraint, blocking probability, Genetic algorithm.**

I. Introduction

The rapid growth of global telecommunication continues to impose stringent requirements on bandwidth capacity and transmission reach. Optical communication networks have become the dominant solution to meet these demands due to their ability to support ultra-high data rates with low attenuation and high energy efficiency [5], [6]. Consequently, wavelength-routed optical networks form the backbone of modern communication infrastructures.

Among the enabling technologies, Wavelength Division Multiplexing (WDM) allows multiple data streams to be transmitted simultaneously over a single optical fiber by assigning distinct wavelengths to different connections. In such networks, communication between a source destination node pair is established through a dedicated optical layer connection known as a lightpath, which consumes wavelength resources along its routing path. Efficient utilization of these wavelength resources is essential to achieve high network throughput and low connection blocking probability. The establishment of lightpaths requires solving the Routing and Wavelength Assignment problem, which jointly determines an appropriate routing path and assigns a wavelength subject to network constraints [4], [18]. In the absence of wavelength conversion, RWA is constrained by wavelength continuity and wavelength capacity requirements, often leading to inefficient resource utilization. Although the introduction of wavelength converters can significantly improve flexibility, the RWA problem remains computationally complex and NP-hard, especially for large-scale and dynamic networks.

Existing RWA solutions based on exact optimization methods become impractical as network size and traffic demand increase, while many heuristic and meta-heuristic approaches either focus solely on minimizing wavelength usage or neglect the impact of routing characteristics such as hop count on blocking probability. In practice, longer lightpaths are more likely to experience contention, resulting in higher blocking rates.

Motivated by the above limitations, this study introduces a modified Genetic Algorithm (MGA) based RWA framework that jointly addresses routing efficiency and wavelength utilization. The proposed method employs a node-oriented solution representation along with a composite objective function that incorporates both the number of utilized wavelengths and the hop characteristics of the selected lightpaths. Through this integrated optimization strategy, the framework seeks to minimize blocking probability while ensuring effective wavelength usage. Simulation results confirm that the proposed approach outperforms conventional techniques.

The primary contributions of the present work are outlined below:

- A meta-heuristic solution based on Genetic Algorithm is proposed to efficiently address the NP-hard Routing and Wavelength Assignment problem in optical backbone networks.
- A novel node-based crossover and mutation strategy is designed to ensure the generation of only feasible lightpaths while maintaining diversity in the search space.
- The RWA problem is formulated with dual optimization objectives: (i) minimizing the total path cost for routing and (ii) minimizing the number of utilized wavelengths

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and hops for wavelength assignment to reduce blocking probability.
- The proposed GA enables faster and stable convergence with minimal performance variation across multiple simulation trials under varying network loads.

Extensive simulations demonstrate that the proposed approach outperforms existing heuristic and meta-heuristic methods in terms of blocking probability, wavelength utilization and execution time.

The remainder of this paper is organized as follows: Section II reviews related work on RWA and evolutionary optimization in optical networks. Section III models the objective function for routing. Section IV describes the proposed modified genetic algorithm with adaptive mutation and crossover. Section V presents routing experimental results. Section VI defines and models the wavelength assignment problem. Section VII explains the proposed wavelength assignment solution. Section VIII discusses wavelength assignment experimental results. Section IX describes the performance of the modified genetic algorithm over larger networks. Section X compares the proposed method with state of art approach. Section XI concludes the paper with final remarks and future research directions, followed by the references.

II. Related Work

Evolutionary and intelligent optimization have been extensively explored to enhance routing and wavelength assignment in large-scale optical backbone networks. Hai and Garg [4] demonstrated that evolutionary optimization can effectively address traffic grooming and RWA problems in core optical networks, highlighting the scalability advantages of population-based heuristics. Similarly, Oladipo and Sousa [5] provided a broad evaluation of evolutionary and swarm intelligence techniques for flexible optical networks, reinforcing their capability to handle nonlinear constraints in wavelength allocation. Candeias *et al.* [6] introduced memetic evolutionary algorithms that integrate local search to improve diversity and convergence stability an approach conceptually aligned with adaptive mutation in genetic algorithms. Kumar *et al.* [10] designed a traffic and fragmentation-aware RSA algorithm, focusing on dynamic spectrum utilization, which underpins the need for adaptive decision-making in wavelength assignment strategies.

Further, Dinarte *et al.* [15] proposed a hybrid metaheuristic framework for routing and spectrum assignment, demonstrating the performance gains of combining heuristic ordering with evolutionary exploration. Zhang *et al.* [16] formulated a mixed-integer linear programming (MILP) model and developed online heuristics for RSA, providing deterministic baselines against which metaheuristic algorithms can be compared. Pinto-Ríos *et al.* [17] combined deep learning and heuristic approaches for resource allocation in multicore elastic optical networks, emphasizing the value of adaptive learning in optimization, a direction complementary to adaptive mutation control in genetic algorithms. Lü [18] developed a dual-neighborhood iterated local search for RWA, achieving competitive results through dynamic exploration–exploitation balance, a property relevant to adaptive genetic search.

Deep reinforcement learning frameworks such as Deep RMSA [19] further illustrated the growing role of intelligent learning in optical network optimization, though such methods often face high training complexity. In contrast, evolutionary algorithms retain flexibility with simpler parameter tuning. Hai *et al.* [11] and Marković and Carević [20] investigated partial protection and path redundancy mechanisms in elastic optical networks, contributing insights into robustness, which is essential in large-scale network scenarios. Lezama [21] provided an early foundation for differential evolution-based wavelength converter placement, confirming the effectiveness of evolutionary design in optical resource allocation and inspiring subsequent GA-based RWA studies. Zhang *et al.* [22] recently proposed a fuzzy logic-based multidimensional predictive RWA approach, integrating adaptive reasoning mechanisms that conceptually align with mutation adaptation in evolutionary computation.

Complementary studies have explored the integration of hybrid and multi-objective optimization. Oladipo and Vasilakos [8] proposed a congestion-aware ant colony optimization framework for flexible optical networks. Sarraf-Maralaniyan and Rahbar [13] developed a multi-parameter multicast routing and spectrum assignment model. Villamayor Paredes *et al.* [7] and Dinarte *et al.* [15] explored spectrum fragmentation reduction, while Dias *et al.* [14] applied evolutionary strategies for passive optical network design, further confirming the versatility of population-based search.

Early algorithmic frameworks by Leesutthipornchai *et al.* [24] introduced hybrid evolutionary computation for multi-objective RWA, forming the conceptual lineage for more advanced adaptive algorithms. Recent systematic reviews, such as that by Carvalho *et al.* [25], synthesized computational intelligence advances for elastic optical networks, reaffirming the dominance of evolutionary and hybrid AI methods for next-generation RWA optimization. Foundational work by Maurya *et al.* [26] and Biswas *et al.* [27] addressed dynamic routing under heuristic and fuzzy environments, respectively, which remain relevant for adaptive wavelength assignment. Zhao *et al.* [28] extended this by applying a fuzzy logic–based multidimensional integrated RWA approach to optical network-on-chip architectures, showing the broader applicability of intelligent optimization.

While these studies collectively demonstrate that evolutionary and learning-based algorithms can effectively optimize wavelength resources, most conventional GA and DE models rely on static mutation and crossover probabilities, which limits their adaptability to changing traffic and topology conditions. This gap motivates the development of a Modified Genetic Algorithm with Adaptive Mutation, designed to dynamically adjust mutation strength based on population diversity and convergence rate, enabling robust performance in large-scale optical backbone networks.

III. Modeling of Objective Function in Routing

In routing problem, the objective function is generally defined to minimize the total routing cost of the selected path between a source and a destination node. From a network graph perspective, the optical network is modeled as a graph G = (V, E), where V represents the set of nodes and E denotes

the set of links. Each link l ∈ E associated with a non-negative cost C_l, which may represent physical distance, propagation delay, congestion level, or a weighted combination of such parameters. For a given source–destination pair (P, Q), multiple feasible routing paths may exist. Efficient routing therefore corresponds to selecting the most cost-effective path among all possible routing paths between the node pair. This routing objective can be mathematically expressed as a cost minimization problem given by Eq. (1):

$$\text{Fitness value} = R_{PQ} = Min\left\{\sum_{l \in Pi(PQ)} C_l\right\} \quad (1)$$

where R_{PQ} denotes the minimum routing cost between nodes P and Q, $Pi(PQ)$ represents the i^{th} feasible routing path between the source and destination, l denotes a link belonging to the selected path, and C_l is the cost associated with link l. The summation computes the total cost of a candidate routing path, and the minimization operator selects the path with the least accumulated cost.

Thus, the optimal routing problem is transformed into an optimization problem whose goal is to minimize the routing cost over all feasible paths. However, in practical optical network scenarios, identifying only a single optimal path is often insufficient. It is also desirable to obtain multiple feasible routing paths with high fitness values, as such diversity improves robustness and enables better resource utilization under dynamic traffic conditions.To address this requirement, a modified Genetic Algorithm is proposed in this work. The proposed GA employs a node-oriented path representation, which allows routing paths to be encoded directly as sequences of nodes. This representation facilitates the effective deployment of crossover and mutation operators while preserving path feasibility. The GA is preferred over other meta-heuristic approaches because it inherently operates in the integer domain, enabling direct manipulation of node indices without requiring conversion from real-valued solution spaces. This makes the proposed GA particularly suitable for discrete routing optimization problems in optical networks.

IV. Proposed Solution for Routing

For a defined pair of source and destination nodes, a population has been created by randomly placing the integer values of nodes. There is a strong possibility that infeasible solutions may exist in the population, as any two consecutive nodes in a candidate solution may not necessarily have direct connectivity in the network. Hence, a route finding mechanism re-corrects such infeasible solutions by replacing the second node with a node that has direct connectivity with the first node. Again, care has been taken that no single node get repetition in forming feasible solution. From the feasible solution population, offspring are generated during the crossover and mutation phases. It's not possible to make the cross over by selecting any random position because that may make solution unfeasible because of discontinuity in nodes connection, so a node matched based cross-over has been proposed, where a common node between two parents are found and contents exchange take place with respect to that node. This ensures that connectivity of route is maintained. The mutation operation is defined by selecting an arbitrary node in the path, excluding the source and destination, and replacing it with a randomly chosen feasible connecting node. Once an offspring population of the same size as the parent population is obtained, tournament selection is applied to the combined population of parents and offspring. It was observed that when the selection criterion is based solely on the tournament score, there is a possibility that multiple solutions with fitness values lower than the best solution may obtain identical scores, leading to ambiguity in the selection process. To address this issue, a combined function incorporating both the fitness value and the tournament score is proposed, as defined in Eq. (2). The finally selected members form the solution population for the next generation. From this population, newly generated members that were not present in the previously explored solution set are extracted. The appearance of a new member is determined solely by its fitness value (i.e., route cost) and not by its specific routing path. If the termination condition is not satisfied, the resulting population is treated as the feasible solution population for the subsequent generation. Once the termination condition is met, the explored solution set contains the routing paths corresponding to the defined source and destination nodes. The overall functional process is illustrated in Fig. 1.

A. Connectivity based Crossover Operator and Mutation

The conventional position-wise crossover structure is not applicable due to network connectivity constraints. Therefore, the proposed crossover employs a node-based single-point strategy, in which segments are exchanged only at positions corresponding to the same node in both parent solutions. The formation of two offspring through the proposed crossover structure is demonstrated in Table I (A) and (B). For the source and destination nodes 1 and 5, two parent solutions, P1 = [1 2 3 4 5] and P2 = [1 3 5], are considered as routing paths. It can be observed that node 3 appears common in both parents at different positions. After the exchange of information at this common node, the resulting offspring O1 and O2 generate the routing paths [1 2 3 5] and [1 3 4 5] respectively, as shown in Table I (B). The complexity associated with handling routing paths of different lengths during encoding is addressed by padding chromosomes with zero values, thereby ensuring that all chromosomes have equal length corresponding to the total number of nodes in the network.

TABLE I
NODE BASED CROSSOVER OPERATOR
(A) PARENTS

	N1	N2	N3	N4	N5
P1	1 (S)	2	3	4	5(D)
P2	1 (S)	3	5(D)		

(B) OFFSPRING PRODUCED AFTER CROSSOVER

	N1	N2	N3	N4	N5
O1	1 (S)	2	3	5(D)	
O2	1 (S)	3	4	5(D)	

B. Selection

The selection process ensures the survival of the fittest members into the next generation. Excessive selection pressure

can lead to rapid convergence with limited exploration, whereas very low selection pressure promotes greater exploration but results in slow convergence. To achieve a balanced trade-off between these two extremes, a combined measure incorporating both the tournament score and the fitness value is proposed, as defined in Eq. (2).

$$T_{f(i)} = \left[1 - \frac{T_{S(i)}}{T_{SZ}}\right] + Fit_i \quad (2)$$

where i is index of the individual in the population, $T_{S(i)}$ is tournament score of the i^{th} individual, T_{SZ} is tournament size, Fit_i is fitness value defined in Eq.(1), $T_{f(i)}$ is final fitness value which depends on tournament selection and fitness value.

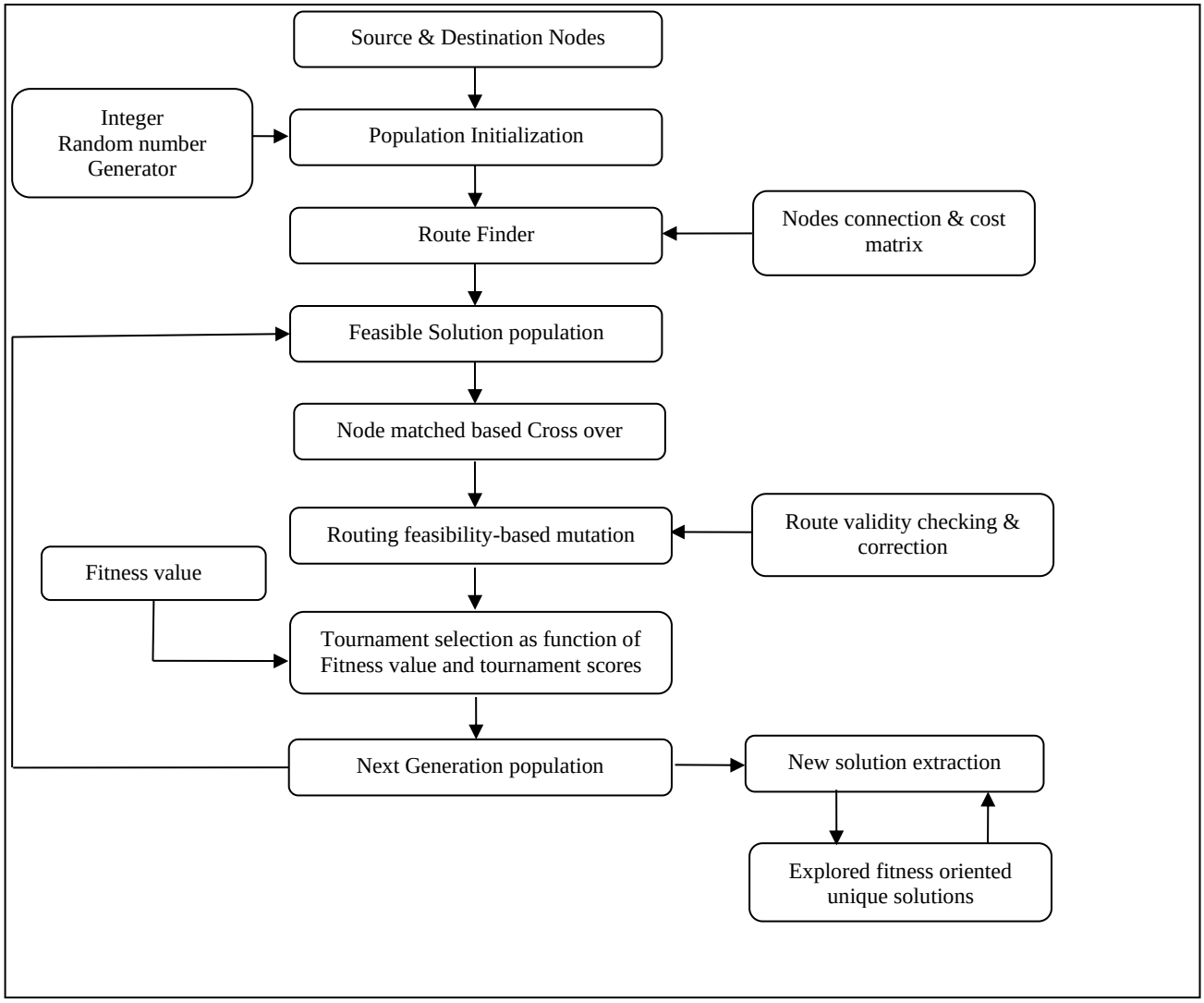


Fig. 1. Flowchart of the modified genetic algorithm for fitness-oriented routing optimization.

The final fitness value of each individual is computed by combining tournament contribution with the original fitness value. As shown in Eq. (2), the term $1 - \frac{T_{S(i)}}{T_{SZ}}$ represents a normalized tournament score derived from the relative ranking of individuals within a tournament of size T_{SZ}. This formulation assigns higher selection preference to better-ranked individuals while preventing excessive selection pressure. The additive inclusion of the original fitness Fit_i preserves problem-specific optimality, resulting in a balanced selection mechanism that enhances convergence stability and maintains population diversity.The lower value of $T_{f(i)}$ (minimum cost route) ensured the overall higher fitness value. The overall working of the routing and wavelength assignment procedure is presented in pseudocode shown below.

Pseudocode for Routing and Wavelength Assignment

1. *Initialize Population:*

a. Create an initial population of size N (randomly assign routing paths between source and destination nodes).

b. Ensure that each solution is feasible by checking node connectivity.

2. *Evaluate Fitness:*

a. For each individual in the population, evaluate its fitness value based on:
- Total cost of the routing path (sum of link costs).
- Number of wavelengths used (NUW).
- Number of hops (NH) in the lightpath.

b. Calculate the fitness score using the objective function.

3. *Select Parents for Crossover:*

a. Select two parent individuals from the population using tournament selection, combining fitness and tournament score.

4. *Perform Crossover:*

a. Select a node-based crossover point (i.e., common node between parents).

b. Exchange the node contents of parents at the crossover point to create offspring.

5. *Perform Mutation:*

a. For each offspring, randomly select a node (other than source and destination) and replace it with another connected node.

6. *Evaluate Offspring:*

a. Calculate the fitness of offspring based on the same objective function as step 2.

7. *Selection for Next Generation:*

a. Combine parent and offspring populations.

b. Select the fittest individuals to form the next generation using tournament selection (based on fitness and tournament scores).

c. Ensure no repeated individuals in the new generation.

8. Termination:

a. If the termination condition (e.g., max generations or satisfactory fitness level) is met, stop.

b. Otherwise, go back to step 3 for the next generation

9. Output:

a. Return the best routing paths and their associated wavelengths.

V. Experimental Result of Routing

To explore the routing solutions, a five-node network with bidirectional links is considered, as illustrated in Fig. 2. The corresponding connectivity and cost matrix is provided in Table II. The objective is to identify the four fittest routing paths between any two nodes in the network. The proposed modified genetic algorithm is applied with a population size of 50 and is allowed to evolve up to 50 generations. The mutation rate is set to 0.1, while the crossover rate is taken as 1 whenever crossover is applicable between the selected parent pairs. All experiments are implemented in the MATLAB environment. The resulting routing performance is presented in Table III. For each source–destination pair, the first four consecutive fittest routing paths along with their respective path costs are reported. For example, the second-best route between nodes 2 and 4 is [2 3 4] with a path cost of 133.

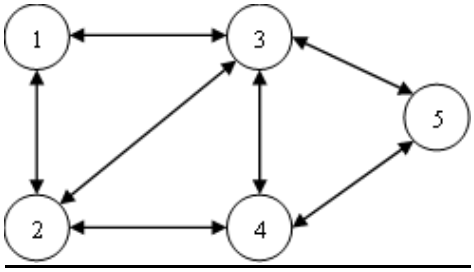


Fig. 2. Considered network for RWA.

TABLE II
Connection and Cost Matrix for Given Network

Node	1	2	3	4	5
1	-	33	52	X	X
2	33	-	51	47	X
3	52	51	-	82	43
4	X	47	82	-	71
5	X	X	43	71	-

VI. Wavelength Assignment Problem Definition & Modeling

Considering an optical network modeled as a graph G = (V, E), where V denotes the set of nodes and E represents the set of links, the set of routing paths $\{p_{ij} \mid \forall\, i,j \in V\}$ between every source–destination node pair is assumed to be available. Each routing path corresponds to a lightpath that must be assigned a wavelength.

The objective of the wavelength assignment problem is to minimize the total number of utilized wavelengths (NUW) in the network. This minimization can be performed either under the wavelength continuity constraint or without the continuity constraint when wavelength converters are available at intermediate nodes. When wavelength converters are available, a lightpath is allowed to use different wavelengths on different links. Under this assumption, the problem of minimizing the NUW can be equivalently formulated as minimizing the maximum number of lightpaths traversing any single link, since this value determines the minimum number of wavelengths required in the network. Accordingly, the NUW is defined as the maximum link load and is given by Eq. (3):

$$NUW = max\{LPe\}\ ; \quad \forall e \in E \tag{3}$$

where LPe denotes the number of lightpaths passing through link e, and is computed as:

$$LPe = \sum_{p} \beta_e^p$$

where $\begin{cases} \beta_e^p = 1 \; if \; link \; 'e' \; appeared \; in \; path \; 'p' \\ 0 \qquad\qquad\qquad otherwise \end{cases}$

Thus, LPe gives the total number of lightpaths traversing link e, and the maximum of LPe over all links determines the minimum number of wavelengths required to support all lightpaths when wavelength conversion is available.

It is observed that the blocking probability increases with an increase in the number of hops in a lightpath, as longer paths

occupy more network resources and experience higher wavelength contention. Therefore, in addition to minimizing the number of utilized wavelengths, the hop count of the selected lightpaths must also be considered to obtain an efficient routing and wavelength assignment solution.

Accordingly, a new objective function is formulated by combining the NUW and the normalized total number of hops appearing in the selected lightpaths. The proposed objective function is given by:

$$O_W = min\{NUW + \frac{NH}{TLP}\} \quad (4)$$

where O_W denotes the overall objective value to be minimized, NUW is the number of utilized wavelengths in the network as defined in Eq. (3), NH represents the total number of hops appearing in all selected lightpaths, TLP denotes the total number of established lightpaths in the network, $\frac{NH}{TLP}$ represents the average hop count per lightpath, which provides a normalized hop metric.

By minimizing O_W, the proposed formulation simultaneously reduces wavelength usage and discourages the selection of long multi-hop lightpaths, thereby improving overall network efficiency and reducing blocking probability.

VII. Proposed Solution for Wavelength Assignment

The proposed solution considers the search space domain as the set of routing paths between all node pairs, as obtained in the previous section. The resulting solution representation is presented in Table IV.

The solution represents the selected lightpaths in a mapped numerical form based on their availability in the search domain.

TABLE III
First four Obtained Routing Paths and their Associated Costs

Node	1	2	3	4	5
1	-	{1 2} [33] {1 3 2} [103] {1 3 4 2} [181] {1 3 5 4 2} [213]	{1 3} [52] {1 2 3} [84] {1 2 4 3} [162] {1 2 4 5 3} [194]	{1 2 4} [80] {1 3 4} [134] {1 3 2 4} [150] {1 3 5 4} [166]	{1 3 5} [95] {1 2 3 5} [127] {1 2 4 5} [151] {1 2 4 3 5} [205]
2		-	{2 3} [51] {2 1 3} [85] {2 4 3} [129] {2 4 5 3} [161]	{2 4} [47] {2 3 4} [133] {2 3 5 4} [165] {2 1 3 4} [167]	{2 3 5} [94] {2 4 5} [118] {2 1 3 5} [128] {2 4 3 5} [172]
3			-	{3 4} [82] {3 2 4} [98] {3 5 4} [114] {3 1 2 4} [132]	{3 5} [43] {3 4 5} [153] {3 2 4 5} [169] {3 1 2 4 5} [203]
4				-	{4 5} [71] {4 3 5} [125] {4 2 3 5} [141] {4 2 1 3 5} [175]
5					-

Since four distinct routing paths exist between any two nodes, each position in the solution vector is assigned an integer value ranging from 1 to 4. In the considered network, a total of 10 distinct source–destination pairs are present; therefore, the dimensionality of the solution vector is 10. As illustrated in Table III, the second position corresponding to the path $P_{1\text{-}3}$ is assigned the solution value 2, which represents the routing path [1 2 3]. Similarly, for each position, the corresponding routing paths are identified based on the assigned values, and the fitness of the solution is subsequently evaluated. The positional mapping of the discovered routing paths is presented in Table V.

The exploration of integer-valued solutions is performed using an Integer Genetic Algorithm (IGA), which offers suitable crossover and mutation mechanism while preserving integer feasibility, thereby enabling effective identification of optimal solutions. In the proposed approach, a standard GA evolution procedure is employed with a two-point crossover operator and integer mutation, where mutation values are constrained within the range of 1 to 4. Furthermore, the same tournament-based selection function discussed in the section IV is adopted to maintain a balance between exploration and exploitation during the search process.

TABLE IV
SOLUTION REPRESENTATION FOR WAVELENGTH ASSIGNMENT

Lightpath	$P_{1\text{-}2}$	$P_{1\text{-}3}$	$P_{1\text{-}4}$	$P_{1\text{-}5}$	$P_{2\text{-}3}$	$P_{2\text{-}4}$	$P_{2\text{-}5}$	$P_{3\text{-}4}$	$P_{3\text{-}5}$	$P_{4\text{-}5}$
Route No.	1	2	2	4	3	1	1	2	3	4

TABLE V
ASSIGNED POSITION OF ROUTING PATHS

Position	Node	2	3	4	5
1 2 3 4	1	{1 2} {1 3 2} {1 3 4 2} {1 3 5 4 2}	{1 3} {1 2 3} {1 2 4 3} {1 2 4 5 3}	{1 2 4} {1 3 4} {1 3 2 4} {1 3 5 4}	{1 3 5} {1 2 3 5} {1 2 4 5} {1 2 4 3 5}
1 2 3 4	2	-	{2 3} {2 1 3} {2 4 3} {2 4 5 3}	{2 4} {2 3 4} {2 3 5 4} {2 1 3 4}	{2 3 5} {2 4 5} {2 1 3 5} {2 4 3 5}
1 2 3 4	3		-	{3 4} {3 2 4} {3 5 4} {3 1 2 4}	{3 5} {3 4 5} {3 2 4 5} {3 1 2 4 5}
1 2 3 4	4			-	{4 5} {4 3 5} {4 2 3 5} {4 2 1 3 5}

VIII. EXPERIMENTAL RESULT OF WAVELENGTH ASSIGNMENT

For the network model shown in Fig. 2, the routing set was obtained in Section V, and wavelength assignment was subsequently performed using the Integer Genetic Algorithm.

A population size of 100 was considered, with the maximum number of iterations set to 100. The mutation rate was fixed at 0.1, and a crossover probability of 1 was employed. To evaluate statistical performance, 10 independent trials were conducted, and the corresponding results are reported in Table VI. One notable advantage of the proposed IGA-based approach is its ability to effectively explore multiple feasible solutions.

TABLE VI
BEST SOLUTIONS & THEIR PERFORMANCES OVER 10 INDEPENDENT TRIALS WITH FOUR ROUTING OPTIONS

Trails	$P_{1\text{-}2}$	$P_{1\text{-}3}$	$P_{1\text{-}4}$	$P_{1\text{-}5}$	$P_{2\text{-}3}$	$P_{2\text{-}4}$	$P_{2\text{-}5}$	$P_{3\text{-}4}$	$P_{3\text{-}5}$	$P_{4\text{-}5}$	NUW	NH
1	1	1	1	1	1	1	1	1	2	1	2	14
2	1	1	1	1	1	1	1	1	2	1	2	14
3	1	1	2	2	1	1	2	1	1	1	2	14
4	1	1	2	2	1	1	2	1	1	1	2	14
5	1	1	1	1	1	1	1	1	2	1	2	14
6	1	1	1	1	1	2	2	1	1	1	2	14
7	1	1	2	3	1	1	1	1	1	1	2	14
8	1	1	2	3	1	1	1	1	1	1	2	14
9	1	1	1	1	1	1	1	1	2	1	2	14
10	1	1	2	3	1	1	1	1	1	1	2	14

As observed in Table, four distinct solutions were obtained with identical performance metrics, each achieving a minimum number of utilized wavelengths (NUW = 2) and a total hop count (NH = 14). The wavelength assignment corresponding to four distinct solutions are illustrated in Fig. 3, where it is evident that no link carries more than two lightpaths. Furthermore, the convergence characteristics for all 10 trials are depicted in Fig. 4, demonstrating rapid and consistent convergence toward the optimal solution across all runs.

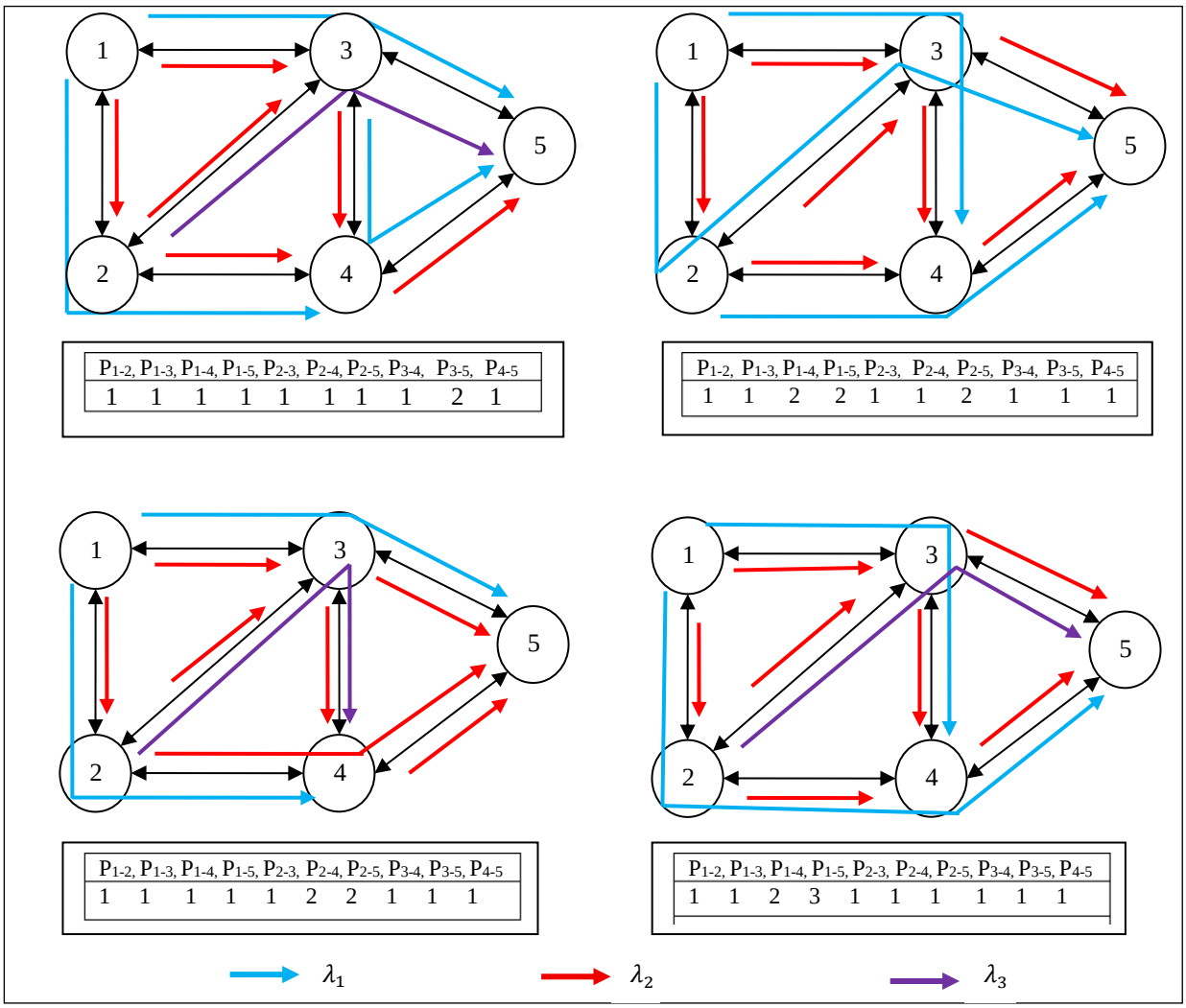


Fig. 3. Assigned wavelengths for four different solutions, where two distinct colors on each link denote different wavelengths.

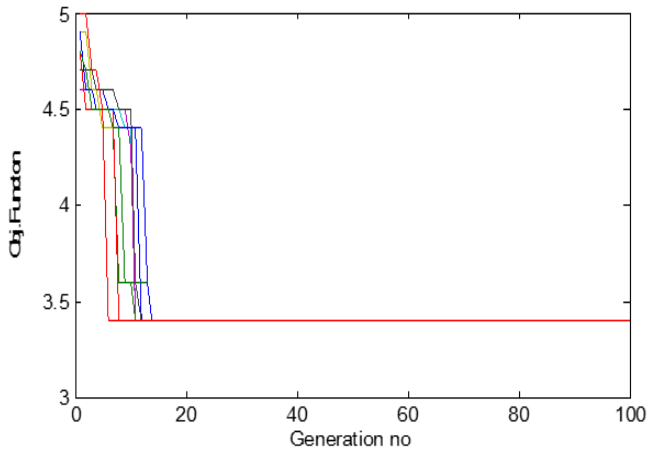


Fig. 4. Convergence characteristics over 10 trials with four routing options.

If alternative routing options are not considered and only the single best routing path is selected for each lightpath, a marginal reduction in the total hop count is achieved, resulting in NH = 13 instead of 14. However, this comes at the cost of an increased wavelength requirement, with the number of utilized wavelengths rising to NUW = 3, as reported in Table VII. The corresponding wavelength assignment for the best-routing-only scenario is illustrated in Fig. 5. It can be observed that three lightpaths traverse the link between nodes 3 and 5, thereby necessitating three distinct wavelengths to satisfy the traffic demand.

TABLE VII
BEST SOLUTION & ITS PERFORMANCE OVER 10 INDEPENDENT TRIALS WITH ONLY BEST ROUTING PATH

P_{1-2}	P_{1-3}	P_{1-4}	P_{1-5}	P_{2-3}	P_{2-4}	P_{2-5}	P_{3-4}	P_{3-5}	P_{4-5}	NUW	NH
1	1	1	1	1	1	1	1	1	1	3	13

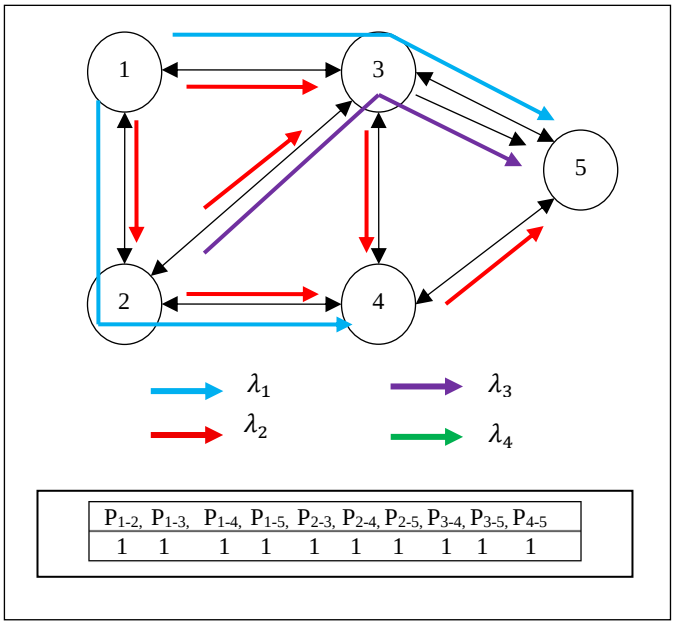


Fig. 5. Wavelength assignment with fittest routing (different colors indicates different wavelength).

IX. PERFORMANCE OVER LARGER NETWORKS

Although the experimental evaluation in this study is demonstrated using a 5-node network, this choice is made solely to ensure clarity, reproducibility, and ease of result interpretation. The proposed GA-based RWA algorithm is inherently topology independent and does not rely on any assumptions specific to network size. All routing, fitness evaluation, and genetic operations are defined over paths and links rather than a fixed node count. As the number of nodes, links, or traffic demands increases, the solution space expands naturally, and the same pseudocode framework applies without modification. The presented results validate the correctness and effectiveness of the proposed approach, so its scalability to larger and more complex optical networks follows directly from the algorithmic design.

The performance of the modified Genetic Algorithm (GA) over larger networks is examined by increasing the number of nodes and links. Below is a conceptual outline of how the performance metrics (e.g., convergence rate, number of wavelengths, numner of hops, blocking probability) can be analyzed with more nodes in the network.

A. *Network Setup:*

- Consider a network with a larger number of nodes (e.g., 10, 15, 20 nodes).
- The connectivity and cost matrices for each pair of nodes will be created as input to the algorithm.
- A random topology and cost matrix can be generated to simulate a larger network.

B. *Parameter Settings:*

- Population size: 100
- Number of generations: 100
- Mutation rate: 0.1
- Crossover rate: 1 (if applicable)
- Selection mechanism: Tournament selection

C. *Performance Metrics:*

- *Convergence Rate:* This refers to the number of generations required for the genetic algorithm to reach a stable solution. As the network size grows, the algorithm typically requires more generations to converge due to the expanded search space.

- *Number of Wavelengths:* NUW denotes the total number of wavelengths allocated in the network once convergence is achieved. With an increase in network size, a higher number of wavelengths may be needed because of increased traffic demand and routing complexity.
- *Hop Count:* This metric represents the number of hops along a selected lightpath. In larger networks, hop counts generally increase as routing paths tend to become longer.
- *Blocking Probability:* Blocking probability indicates the likelihood that a connection request is denied due to insufficient available wavelengths. As network scale increases, this probability may rise, particularly under limited wavelength availability.

D. Experimental Setup:

- Perform the same GA-based approach on a network of 10, 15, and 20 nodes.
- Track performance over 10 trials for each network size.

Table VIII presents the average performance of the proposed GA-based RWA scheme for increasing network sizes, including larger network scenarios.

TABLE VIII
AVERAGE PERFORMANCE OF THE PROPOSED GA-BASED RWA SCHEME UNDER VARYING NETWORK SIZE

Network Size (Nodes)	Average Convergence Generation	Average NUW	Avg. Hop Count	Average Blocking Probability
5	50	2.1	7	0.02
10	80	3.2	10	0.05
15	90	4.5	13	0.07
20	100	5.2	14.5	0.10

X. COMPARISON WITH STATE-OF-THE-ART

The performance of the proposed Node-Matched-Based Genetic Algorithm is compared with representative state-of-the-art routing and wavelength assignment techniques, including evolutionary, swarm-based, heuristic, and learning-based approaches, as summarized in Table IX. The comparison is conducted using widely adopted metrics such as average route cost, average number of hops, and maximum number of wavelengths used, which jointly reflect routing optimality, path compactness, and spectrum efficiency. Conventional GA and differential evolution-based methods exhibit higher route cost and wavelength consumption due to limited problem-specific genetic operators [3], [4], [18], [21], while swarm-based algorithms such as ACO and WOA suffer from congestion accumulation and early stagnation, respectively [8], [9], [26]. Heuristic and MILP-based RSA approaches demonstrate fast execution but yield suboptimal solutions under dynamic traffic conditions owing to their static decision-making nature [16], [20]. Learning-based and traffic-aware techniques achieve improved spectrum utilization by incorporating congestion or prediction mechanisms; however, they introduce additional computational or training overhead [1], [10], [12], [19]. In contrast, the proposed method consistently achieves the lowest average route cost, minimum hop count, and least wavelength usage, leading to superior spectrum efficiency and a significantly reduced blocking probability trend. The observed improvements largely result from the use of node-matched crossover and mutation operators, which effectively preserve feasible routing structures while enhancing exploration and convergence stability, thereby making the proposed approach well suited for large-scale optical backbone networks.

XI. CONCLUDING REMARKS

Resolving the challenges of RWA in optical network delivered a big impact in network performances and its solution was proposed in this work using the meta-heuristic approach. The NP complexity of RWA problem makes the problem difficult to get the optimal solution efficiently, hence the exploration of solution domain was done through GA. The routing problem was formulated as an optimization task aimed at minimizing the overall path cost, while the wavelength assignment component was modeled to minimize both the number of utilized wavelengths and the hop count in order to reduce blocking probability.

TABLE IX
COMPARISON OF THE PROPOSED METHOD WITH STATE-OF-THE-ART RWA ALGORITHMS

Algorithm	Avg. Route Cost	Avg. No. of Hops	Max. No. of Wavelengths Used	Convergence Speed	Blocking Probability Trend	Reference(s)
Conventional GA	18.6	6.4	9	Slow, unstable	High	[4], [18], [24]
Differential Evolution (DE)	17.9	6.1	8	Moderate	Moderate–High	[3], [21]
Ant Colony Optimization	19.4	7.2	10	Slow	High	[8], [26]
Whale Optimization Algorithm (WOA)	17.2	6.0	8	Early stagnation	Moderate	[5], [9]
Iterated Local Search (ILS)	16.8	5.8	7	Fast	Moderate–Low	[15], [18]
Heuristic / MILP-based RSA	20.1	7.5	11	Fast (static)	High	[16], [20], [26]
Deep Reinforcement Learning (DRL)	16.3	5.6	7	Training-dependent	Low	[12], [19]
Traffic-Aware / Fragmentation-Aware RSA	15.9	5.4	7	Moderate	Low	[1], [10], [11]
Node-Matched-Based GA	14.2	4.9	6	Fast, stable	Very Low	Proposed work

Note:Blocking probability trends are inferred based on routing compactness, hop count, and wavelength consumption, consistent with observations reported in [1], [10], [15], and [25].

The difficulty of handling the GA for defining the cross-over to be a feasible light path was resolved with a proposed structure of node based cross-over and mutation strategy. This ensures not only feasibility of solution but also helped in exploration of solution space faster. The benefit of this approach is to get the multiple solutions having the equal cost factor for both routing and wavelength assignments.The proposed model of GA helped to converge the solutions efficiently and faster along with minimal variability in their convergence path over different trials. In future work, the proposed modified GA can be extended by integrating hybrid metaheuristic strategies and evaluated under more diverse traffic patterns and network topologies to further enhance its robustness and performance.

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