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Parameter Tuning for Genetic Algorithm Applied to Quantum Routing with Multiple Communication Requests Across Two Different Topologies

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ABSTRACT

The quantum internet facilitates communication between quantum devices, making its development essential for advancing quantum technologies. However, realizing a fully functional quantum internet requires overcoming several challenges, including establishing efficient routing mechanisms to ensure effective communication. This study proposes a capacity allocation scheduling scheme based on a Genetic Algorithm (GA) to address the issue of non-uniform edge capacity utilization within a practical routing process. However, it is essential to note that the performance of the GA scheduling scheme is influenced by its control parameters, highlighting the need for parameter tuning. In this paper, we conducted simulations to examine how epochs and population sizes impact the GA scheduling performance, specifically in maximizing average capacity utilization U and weighted throughput F. The configurations were simulated under six and ten communication requests across two topology structures to assess their response to variations in problem characteristics. The simulation results were then compared with an existing capacity allocation scheduling method, Progressive Filling (PF). Our findings reveal that GA outperforms PF in all scenarios and topology structures. Additionally, we deduce that 30 epochs and a population size of 50 are adequate for optimizing average capacity utilization U and weighted throughput F.

1. Introduction

The substitution of classical bits with quantum bits (qubits) in information processing revolutionizes the world by transforming computing and communication systems. The transformation is facilitated by the advancement of various quantum technologies, including quantum computing [1], quantum cryptography [2], and quantum communication [3]. The transformation would significantly impact various fields, such as optimization, cryptography, drug discovery, and higher precision clock synchronization. However, advancements in the engineering aspect of quantum technologies pose a significant challenge to the fundamental purpose of the classical internet, as quantum devices require the ability to transfer quantum information [4]. Therefore, a quantum internet is envisioned as a network facilitating communication primitives

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between quantum devices [5]. However, significant challenges must be overcome before a fully functional quantum internet can be realized, including developing efficient routing mechanisms for effective data transmission.

Given the constraints of limited and non-uniform edge capacity utilization resulting from a finite quantum memory [6], there is a need to design a routing algorithm that efficiently utilizes network capacity within each processing window. Therefore, in this study, we proposed a capacity allocation scheduling scheme based on a Genetic Algorithm (GA) [7], building upon our previous study presented in [8]. This scheme handles multiple communication requests simultaneously, effectively managing the limited network resources. To the best of our knowledge, the proposed GA scheduling scheme is the first quantum routing scheme incorporating a metaheuristic algorithm. A GA is an optimization algorithm inspired by natural selection and genetics principles. The effectiveness of GA in solving a particular optimization problem relies on the selection of its control parameters [9], including population size, epochs, selection mechanisms, crossover rate, and mutation rate. Slight adjustments to these parameters can significantly impact the performance of the GA.

Therefore, parameter tuning is essential for identifying the optimal settings that ensure the proposed GA capacity allocation scheduling scheme operates at its best. This process involves configuring the algorithm to maximize performance for a specific problem instance. In this research, parameter tuning focuses on adjusting the GA's epochs (E) and population sizes (PS) to optimize the capacity allocation scheduling scheme for maximizing average capacity utilization (U) and weighted throughput (F). By concentrating solely on these two parameters, the study adopts a targeted and efficient approach that balances simplicity with effectiveness. Both epochs and population size are critical to the algorithm's performance: epochs directly influence the model's convergence and generalization capabilities, while population size impacts the diversity and exploration efficiency of the GA. Concentrating on the most influential parameters ensures computational feasibility and clarity while effectively addressing critical aspects of the algorithm's behavior. It avoids the complexities and overfitting risks of tuning a broader range of parameters.

Given the sensitivity of GA performance to epochs and population sizes, determining their optimal settings is crucial for the proposed GA capacity allocation scheduling scheme. The objectives of this study are as follows:

i. To investigate the effect of epochs and population sizes on the performance of the GA capacity allocation scheduling scheme.
ii. To analyze the response of the GA capacity allocation scheduling scheme to variations in problem characteristics, such as the number of communication requests and topology structure.
iii. To compare the optimized GA capacity allocation scheduling scheme with the existing capacity allocation scheduling, progressive filling (PF).

The rest of the paper is organized as follows: Section 2 explains the unique features of qubits and investigates the recent research effort in the quantum routing domain. Section 3 presents the proposed solution for the identified problem. Section 4 describes the method to evaluate the performance of the proposed GA capacity allocation scheduling scheme, including the experimental setup and performance measures. Section 5 compares and discusses the simulation results. Section 6 concludes the paper.

2. Literature Review

This section briefly explains the fundamental concept of qubits and investigates recent research efforts within the quantum routing domain.

2.1 Overview of Quantum Information

Qubits serve as the fundamental units of information in quantum technologies. The information encoded in qubits is called quantum information [10]. Some key features of qubits are superposition, quantum entanglement, quantum measurement, and no-cloning theorem.

Superposition: A qubit is a two-state quantum system [11]. It exists simultaneously in two coherent quantum states, $|0>$ and $|1>$. Contrary to the classical bit, which can only represent one of two binary digits, “0” or “1” at a time, superposition enables a qubit to use two quantum states simultaneously. Quantum Measurement: A measurement causes the two-state quantum system to collapse from coherent superposition states to a single, definite state. A measurement irreversibly perturbs the coherent superposition of the quantum system [12]. Quantum measurement is employed to extract numerical data from a quantum system.

Quantum Entanglement: Entanglement is a phenomenon where two or more qubits are ideally linked [13]. Therefore, measuring one pair of the entangled qubits reveals the state of the other pair. No-Cloning Theorem: According to this theorem, a copy of an arbitrary quantum state is impossible to reproduce since the properties of a qubit cannot be measured without leaving its state unchanged [14-16]. The challenge of developing and designing quantum routing lies in effectively harnessing and manipulating these properties.

2.2 Related Work

Communication between nodes in the network can take place via various paths. A routing protocol determines the best path for forwarding data from a source to a destination. Quantum routing utilizes quantum mechanics for efficient information transfer. It plays a crucial role in the development of the quantum internet. Most quantum routing schemes proposed in the literature incorporate classical concepts, including multi-path routing, Dijkstra’s shortest path, and greedy routing. Quantum entanglement is a valuable element in quantum internet as it is used to interconnect quantum nodes, enabling information exchange. Therefore, quantum entanglement has been implemented as a routing metric in several works in [17-19]. However, due to qubits’ delicate nature and susceptibility to environmental decoherence [20,21], maintaining entanglement links for routing purposes poses several challenges that require further investigation.

Moreover, Mina *et al.,* [22] proposed a routing protocol to minimize the time required to regenerate entanglement links between sender and receiver nodes. Li *et al.,* [6] suggested a routing approach facilitating automated responses to numerous entanglement establishment requests, thereby enhancing the efficient generation of entanglement between distant nodes. Furthermore, Gyongyosi *et al.,* [23] presented a decentralized routing method to identify the shortest paths in multi-level entanglement scenarios. Besides that, Gyongyosi *et al.,* [24] proposed an adaptive routing method that employs a base graph to select the shortest paths and determine alternative routes in the event of quantum memory failures.

Pirker *et al.,* [25] introduced the concept of region routing to streamline the process of establishing graph states. Le *et al.,* [26] utilized deep learning techniques in the Deep Quantum Routing Agent (DQRA) to identify optimal routing paths for communication requests. Furthermore, Li *et al.,* [27] proposed an innovative routing technique tailored for single photons with varying frequencies. The technique involves a specific cavity configuration with embedded atoms and channel boundaries designed to manipulate the interaction between photons and atoms to control the routing process. The quantum routing domain is advancing with ongoing studies. Despite several proposed quantum routing schemes, a definitive standard has not yet been established as the field continues to evolve with ongoing studies.

3. Proposed Scheme: Capacity Allocation Scheduling Based on a Genetic Algorithm (GA)

This section explains the proposed capacity allocation scheduling based on a Genetic Algorithm (GA). The GA scheduling processes multiple connection requests concurrently to ensure the network capacity within each processing window is utilized efficiently. It identifies and establishes ten connection paths for each communication request $r = [S_r, D_r]$, where S_r is the source node and D_r is the destination node. The overall process of the routing scheme is summarized in Figure 1.

In the Initialization Phase of each processing window, the network topology $G = (V, E)$ is reinitialized, where V and E represent vertices and edges, respectively. This initialization involves setting the maximal edge capacity, $C_O = 100$ for each edge in the network. Entanglement is then attempted between adjacent nodes. Due to the probabilistic nature of quantum entanglement, the actual capacity realized on any edge may be lower than C_O. The distribution of fidelity values among edges follows a normal pattern with mean $F_{avg} = 0.8$ and standard deviation $F_{std} = 0.1$.

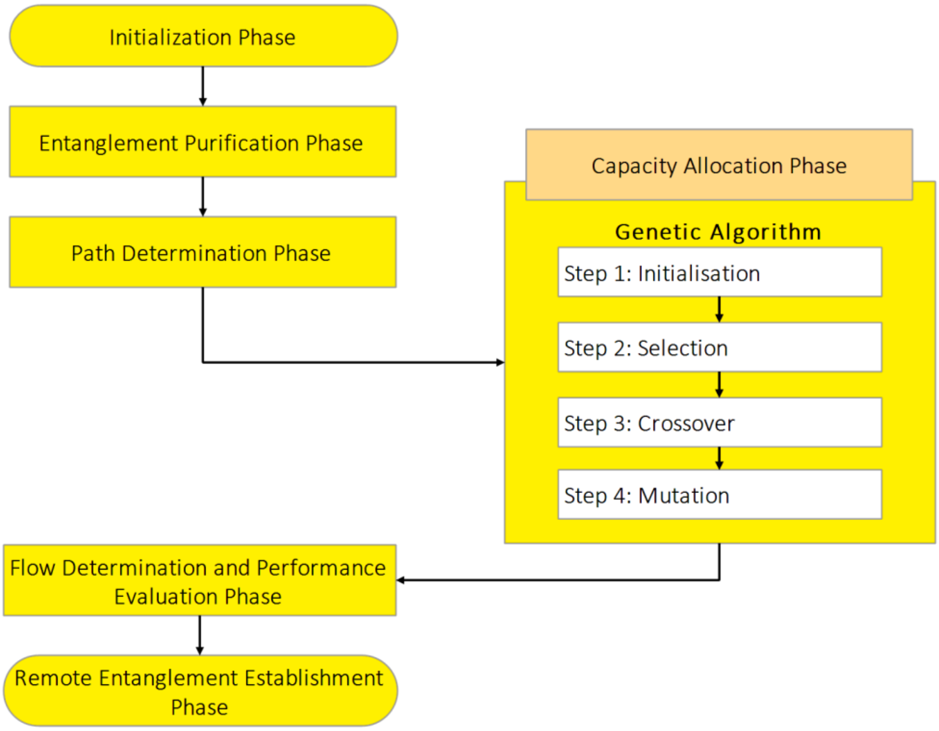


Fig. 1. Summary of the routing scheme: Capacity allocation scheduling scheme based on a genetic algorithm

In the entanglement purification phase, on every edge $(i, j) \in E$ with fidelity below the threshold $F_{th} = 0.8$ and a realized edge capacity $C_{i,j} \leq C_O$, entanglement purification is performed. Additionally, all edges (i, j) with a residual capacity less than the maximum number of paths l_{max} = 10 are terminated and removed from the topology. As a result of entanglement purification and termination of edges, the overall number of edges in the network topology decreases.

In the path determination phase, routes for all communication requests are determined based on the revised network topology, G'. Once this revised topology is prepared, paths are identified for each communication request $r = [S_r, D_r]$ using k shortest paths. Instead of relying on a single shortest path for each connection request, the algorithm identifies ten paths, k, between each source, S_r, and destination, D_r, node pair while considering factors like path length and network conditions to enhance the network's robustness. The choice of paths, k is influenced by specific network conditions as follows: the number of communication requests $|r|$ that must be handled within a time window; the size of the network, precisely the number of edges $|E|$, which determines the network's complexity and capacity for multiple paths; and the maximum network capacity C_O, ensuring that the paths identified can handle the traffic demand without exceeding network resources.

The paths identified are stored in a path information set H, which records details for each edge (i, j) forming part of a path l associated with a request r. Each entry in H is represented as a tuple $[r, l, d, o]$, where r denotes the connection request linked to the path, l is the specific path identified for that request, d is the length (total cost) of the path, and o indicates the order or position of edge (i, j) within the path l, showing its sequence in the route. This structure allows efficient referencing and management of paths, enabling the network to adapt to failures or changes in conditions dynamically.

The primary contribution of this study lies in the capacity allocation phase, which is divided into five essential steps. Step 1 generates an initial population of random individuals (flow on edge). In Step 2, two parents are selected from this population to produce a new flow on edge generation. These selected parents are then paired, and information is exchanged through random crossover points via a crossover operation (Step 3), thereby establishing a new population. Finally, in Step 4, the mutation is applied to the flow on edge of the child to enhance the diversity of the population. The mutant individuals of the flow $\mathrm{f}_{\mathrm{ij}}^{\mathrm{r,l}}$ on each passing edge are evaluated by calculating their fitness function, Ft (see Eq. (3)). The fitness function is the sum of average capacity utilization, U, and weighted throughput, F. The edge capacity of mutant individuals should not exceed the maximum allowed edge capacity $C_{i,j} \leq C_O$. Mutant individuals that meet the constraint are retained in the population; otherwise, they are replaced by parent individuals that meet the criteria.

In the flow determination and performance evaluation phase, the capacity constraints imposed by the network's topology are evaluated, and the final allocated flow is determined. The final allocated capacity flow refers to the actual amount of flow transmitted over a specific path for a given request. When managing network paths, each path associated with a request is subject to certain constraints, particularly regarding the maximum capacity it can handle. Effective capacity allocation ensures data can traverse a network efficiently without bottlenecks in network flow optimization. A vital aspect of this allocation process is the short-board constraint, which dictates that the flow allocated to a path cannot exceed the capacity of its weakest link—meaning the edge within that path that has the minimum capacity. The short-board constraint ensures that the allocated flow remains feasible; if one edge cannot support a certain level of traffic, it limits the overall flow of the entire path. This rule is essential in maintaining the stability and reliability of data transmission across the network.

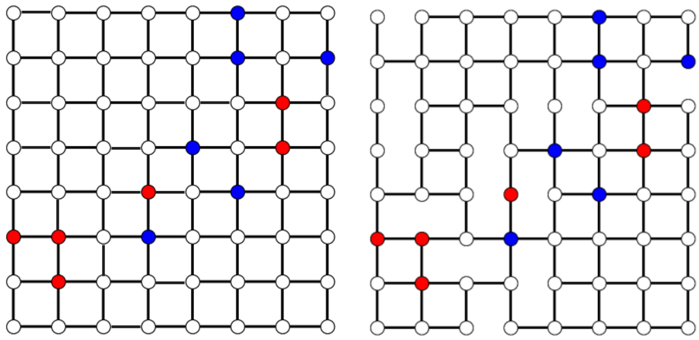
In the end-to-end entanglement establishment phase, entanglement swapping is executed to establish remote entanglement between the specified communication requests. Entanglement swapping involves intermediate quantum nodes acting as repeaters to connect entangled pairs over longer distances. When two adjacent nodes in the network become entangled, the network performs a Bell state measurement on qubits from each pair at an intermediate node. This measurement effectively "swaps" the entanglement, creating a new entangled state between the non-adjacent nodes extending the network's reach. This method is repeated across multiple intermediate nodes until the two remote nodes specified in the connection request are entangled.

4. Methodology

This section describes the method used to evaluate the performance of the GA scheduling scheme.

4.1 Simulation Setup

Simulations were conducted to validate the performance of the proposed GA scheduling scheme. The response of the GA capacity allocation scheduling to variations in problem characteristics was investigated through simulations conducted in four distinct scenarios. Scenario 1 simulates six communication requests (denoted as $6 = [S_6, D_6]$). While Scenario 2 simulates ten communication requests (denoted as $10 = [S_{10}, D_{10}]$). These scenarios were simulated in two different topological structures, namely Topology 1 ($T1$) and Topology 2 ($T2$). Figure 2 shows a sample topology featuring the coordinates of six communication requests (Scenario 1) with corresponding sender and destination nodes–depicted in red and blue, respectively. The illustration captures the topology's structure before and after entanglement purification. Initially, the topology comprises 64 nodes and 112 edges. Following entanglement purification, Topology 1 has a revised total of 99 edges, while Topology 2 has 103 edges. The number of nodes remains constant.



(a) (b)

Fig. 2. A topology sample of six communication requests (a) Topology 1: Initial topology structure (b) Topology 2: Revised topology structure after purification

4.2 Performance Parameters

Just as conventional data routing is assessed, the performance of GA scheduling is evaluated by calculating its average capacity utilization, U and weighted throughput, F. Table 1 lists the notations adopted for computing the performance parameters.

Average Capacity Utilization, U: The amount of routed traffic in the network is evaluated by calculating capacity utilization on every edge (i, j). It is computed using the following Eq. (1):

$$U = \frac{1}{n} \Sigma_{i=0,\ j=0}^{n-1,\ m-1} x_{i,j} \tag{1}$$

where m = length of edge request, n = number of edges, and $x_{i,j} = \frac{\Sigma_{r,l} f_{i,j}^{r,l}}{c_{i,j}} \in (0,1]$.

Table 1
Adopted notations

Symbol	Explanation
$\boldsymbol{l}$	Path
$\boldsymbol{d_{r,l}}$	Path length
$\boldsymbol{P_{in}}$	Probability of success
$\boldsymbol{f^{r,l}}$	Flow
$\boldsymbol{f_{ij}^{r,l}}$	Flow on passing edge (i,j)
$\boldsymbol{C_{ij}}$	Edge capacity on passing edge (i,j)
$\boldsymbol{W_r}$	Weight of request r

Weighted throughput, *F*: Besides capacity utilization, system throughput is another critical parameter to measure the performance of the routing algorithm. In routing terminology, system throughput is equivalent to the entanglement generation rate. The entanglement generation rate represents the number of successfully established entangled pairs in the network within a fixed time window. Considering the weights W_r of each flow, we defined the system throughput associated with different connection requests as the cumulative total of weighted flow across all paths and requests, computed using the following Eq. (2):

$$F = \sum_r W_r \sum_l f^{r,l} P_{in}^{d_{r,l}-1} \tag{2}$$

Fitness function, Ft: Each individual (flow *on edge*) in the population is evaluated by a defined fitness function. The quality of each flow is indicated by its fitness score. A higher-quality flow returns a higher fitness score. Eq. (3) is used to compute the fitness score, which is the sum of average capacity utilization, U and weighted throughput, F.

$$Ft = U + F \tag{3}$$

4.3 Parameter Settings of GA Capacity Allocation Scheduling Scheme

Several epochs (30, 40, 50, 60) and population sizes (50, 70, 90, 110) are used in the simulations to investigate their effect on the GA capacity allocation scheduling performance. The parameter settings used in the simulation scenarios are presented in Tables 2 and 3. A total of 320 simulation runs were conducted. Ten simulation runs are performed for each set of parameters to get the mean value of the average capacity utilization, U and weighted throughput F. The results are averaged to account for the stochastic nature of the quantum system.

Table 2
The parameter settings used to investigate the effect of epochs on GA scheduling

Parameter	Value
Epochs (E)	30, 40, 50, 60
Tournament size (TS)	5
Population size (PS)	50
Number of crossovers	10
Mutation rate (MR)	0.02

*The tournament size (TS) is 10% of the population size (PS)

Table 3
The parameter settings used to investigate the effect of population sizes on GA scheduling

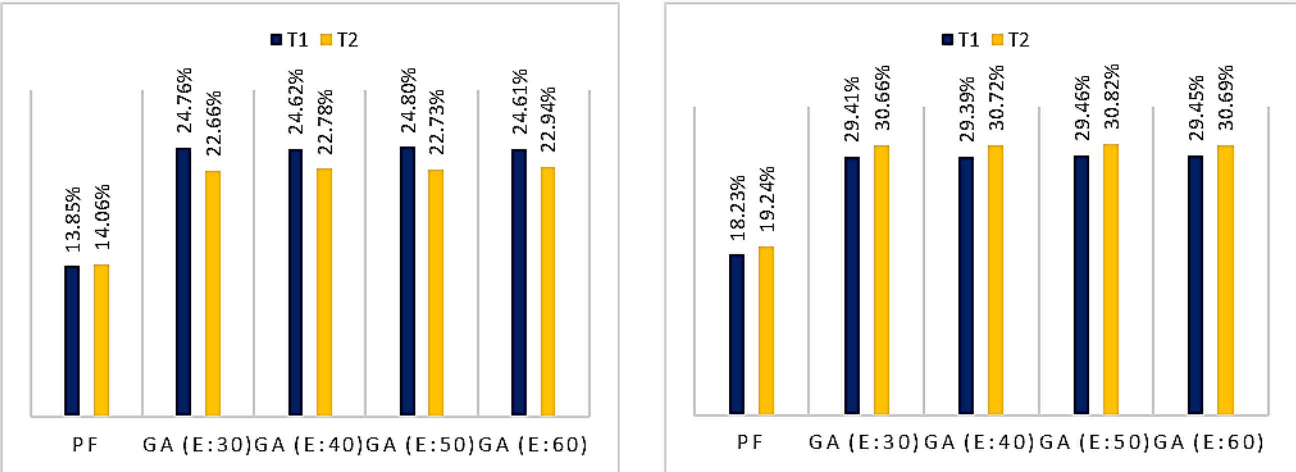
Parameter	Value
Population size (PS)	50, 70, 90, 110
Tournament size (TS)	5, 7, 9, 11
Epochs (E)	30
Number of crossovers	10
Mutation rate (MR)	0.02

*The tournament size (TS) is 10% of the population size (PS)

5. Results and Discussion

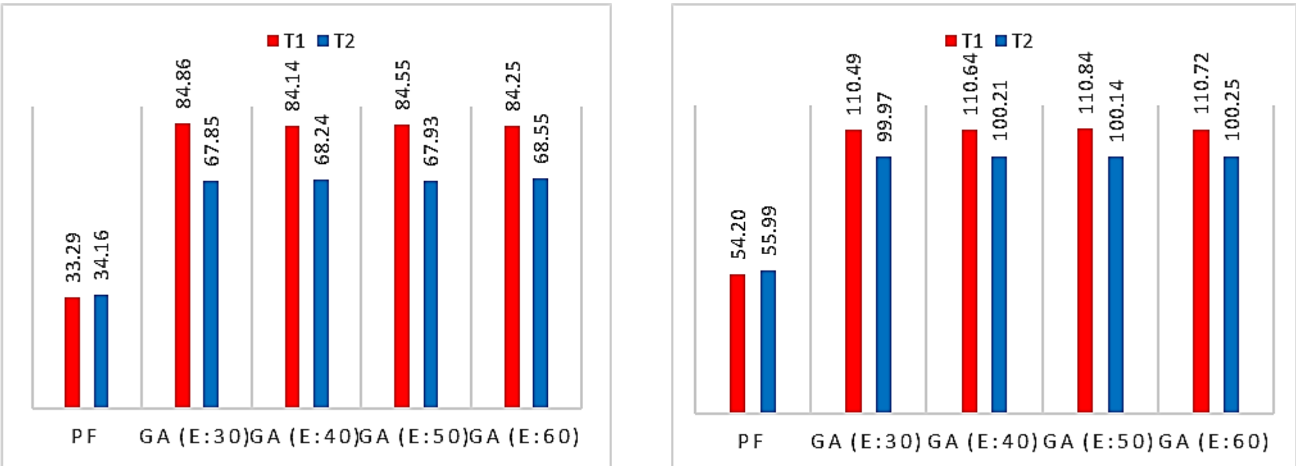
The performance of the proposed GA capacity allocation scheduling scheme is assessed by comparing its average capacity utilization, U and weighted throughput, F with Progressive Filling (PF) [6]. The primary objective of conducting the simulations is to investigate the impact of epochs (E) and population sizes (PS) on the scheduling performance of the GA. Figures 3 to 6 illustrate the results of Scenario 1 and Scenario 2, which involve 6 and 10 communication requests simulated in Topology 1 ($T1$) and Topology 2 ($T2$). The GA scheduling employed parameter settings as presented in Tables 2 and 3.

Figures 3 and 4 illustrate the average capacity utilization, U and weighted throughput, F, respectively, under several epochs (E). Based on the results shown in Figure 3, GA consistently outperforms PF across all epochs. Additionally, the variations in average capacity utilization, U among several epochs, are insignificant. Therefore, we conclude that 30 epochs are sufficient to optimize the average capacity utilization, U.



(a) (b)

Fig. 3. The average capacity utilization, U of GA under several epochs (E), compared with the PF. GA (E: *x*) denotes the simulation result under *x* epochs, where *x* varies as 30, 40, 50, and 60 (a) 6 communication requests (b) 10 communication requests



(a) (b)

Fig. 4. The weighted throughput, F of GA under several epochs (E), compared with the PF. GA (E: *x*) denotes the simulation result under *x* epochs, where *x* varies as 30, 40, 50, and 60 (a) 6 communication requests (b) 10 communication requests

Figure 4 compares the weighted throughput, F results of PF and GA under various epochs. Similar to average capacity utilization, U, the weighted throughput, F results of GA consistently surpass PF throughout all epochs. Since the variations in weighted throughput, F, among several epochs are insignificant, we conclude that 30 epochs are sufficient to optimize the weighted throughput, F.

The average capacity utilization, U and weighted throughput, F results of GA under different population sizes are presented in Figures 5 and 6, respectively. These results are also compared with the PF outcomes. The results shown in Figure 5 depict that GA performance is always better than PF across all population sizes. Compared to PF, GA best exploits edge capacities. Notable, the variations in average capacity utilization, U among several population sizes, are insignificant. Therefore, we conclude that 50 population sizes are sufficient to optimize capacity utilization, as we aim to avoid PF surpassing GA in computation time. It is important to note that a larger population size necessitates more computation search time.

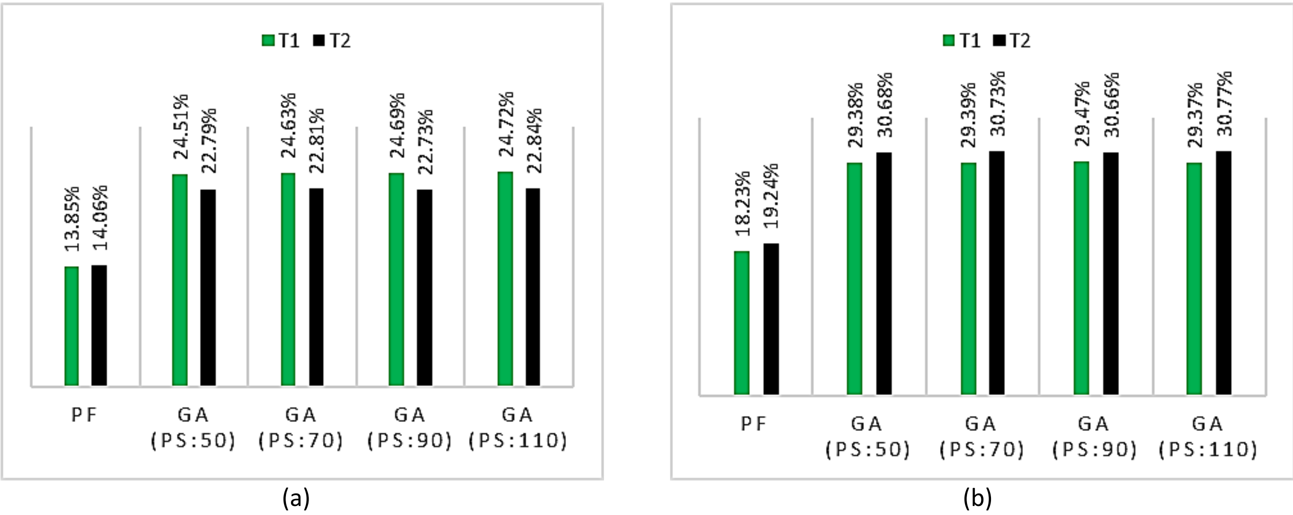


Fig. 5. The average capacity utilization, U of GA under different population sizes (PS), compared with the PF. GA (PS: *y*) denotes the simulation result under *y* population sizes, where *y* varies as 50, 70, 90, and 110 (a) 6 communication requests (b) 10 communication requests

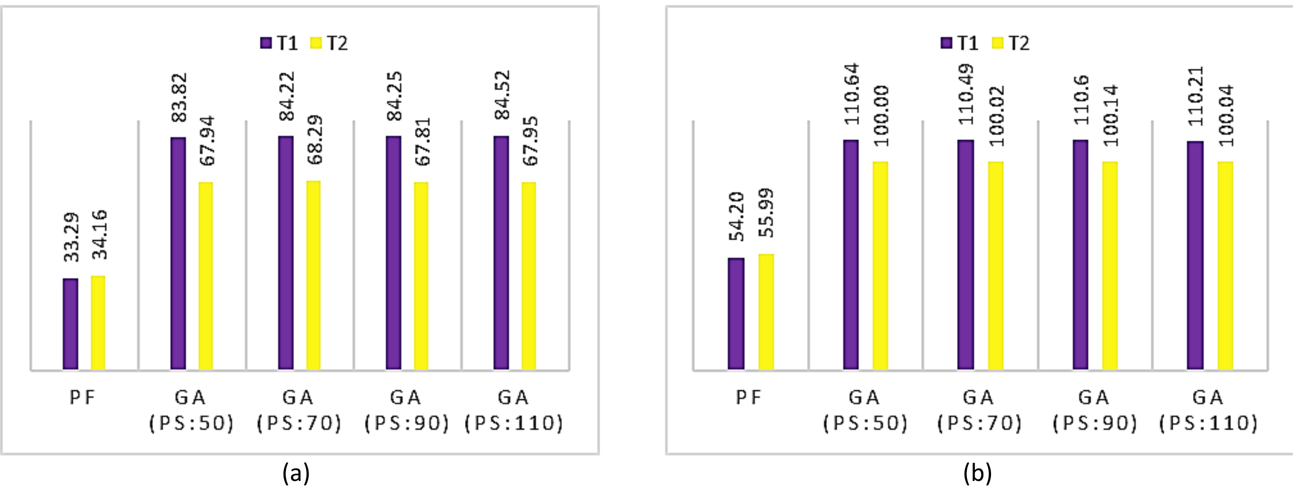


Fig. 6. The weighted throughput, F of GA under different population sizes (PS), compared with the PF. GA (PS: *y*) denotes the simulation result under *y* population sizes, where *y* varies as 50, 70, 90, and 110 (a) 6 communication requests (b) 10 communication requests

In Figure 6, the weighted throughput, F results of PF and GA are compared. The results demonstrate that across population sizes, the performance of GA consistently surpasses that of PF. Given the insignificance of variations in weighted throughput, F results across multiple population sizes, we deduce that 50 population sizes are sufficient for optimizing the system's throughput.

5.1 Applications of the Proposed Genetic Algorithm Scheduling Scheme in the Relevant Domain

This sub-section discusses the potential applications of the proposed GA scheduling scheme. The optimization capabilities of the GA scheduling scheme can be implemented across diverse domains, offering solutions that enhance efficiency, reduce costs, and improve overall system performance. The GA scheduling scheme can optimize schedules in project management timelines that involve numerous interdependent tasks and deadlines. It analyses various task sequences and duration combinations to identify the most efficient schedule. By considering dependencies, task priorities, and resource constraints, the scheme proposes schedules that minimize project duration, maximize resource utilization, and ensure timely task completion. Furthermore, in the investment sector, it can be used for portfolio optimization, guiding the allocation of investment resources based on market conditions.

Next, the scheme optimizes vehicle routing and scheduling in transportation and logistics, ensuring efficient organization of deliveries. By considering critical parameters such as delivery time windows, urgency of deliveries, and the availability of vehicles, the proposed GA scheduling scheme can generate schedules that minimize waiting times, prevent delays, and make optimal use of available resources. It enhances the efficiency of the delivery process, contributing to cost savings and customer satisfaction.

Subsequently, in the network communication domain, the scheme aids in identifying various resource allocation strategies by considering factors such as network traffic patterns, quality of service (QoS) requirements, and data priorities. In network communication, the timing and sequencing of data transmission are crucial to prevent bottlenecks and ensure smooth data flow. The scheduling scheme optimizes resource allocation and schedules data transmission to minimize congestion, improve network performance, and enhance efficiency in delivering diverse communication services.

6. Conclusions

The quantum internet has been proposed to proliferate the advancement of quantum technologies as it facilitates the transmission of quantum information between quantum devices. Numerous challenges must be overcome before a fully functional quantum internet can be realized. This paper addresses the limited and non-uniform edge capacity utilization through a proposed capacity allocation scheduling based on a Genetic Algorithm (GA). As the performance of the GA capacity allocation scheduling scheme is influenced by its parameter settings, parameter tuning is crucial. Therefore, we conducted parameter tuning to investigate the effect of epochs and population sizes on the performance of the proposed GA scheduling scheme. Based on the simulation results, we conclude that utilizing 30 epochs and a population size of 50 is sufficient to optimize the average capacity utilization, U and weighted throughput, F in each scenario.

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