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Optimization of Computer Network Performance Using Heuristic Algorithms

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A B S T R A C T

As the complexity and demand for speed and efficiency in modern computer networks increase, network performance optimization becomes a major challenge in the world of information technology. Issues such as high latency, limited bandwidth, and uneven load distribution often hinder network performance. This research aims to explore and implement heuristic algorithms as a solution to optimize computer network performance. Heuristic algorithms, such as genetic algorithms, ant colony optimization, and particle swarm optimization, offer adaptive and efficient approaches in seeking optimal solutions to complex problems that cannot be solved exactly in a reasonable time. This research conducts simulations of various network scenarios, focusing on optimal route selection, traffic management, and network resource allocation. The simulation results show that the use of heuristic algorithms can increase throughput, reduce delay, and improve bandwidth utilization efficiency compared to conventional approaches. Additionally, the algorithms used are capable of dynamically adapting to changes in topology and network conditions. These findings demonstrate the great potential of heuristic algorithms in managing future networks that are smarter and more responsive. This research provides theoretical and practical contributions to the development of efficient, flexible, and real-time operationally capable network systems.

Keywords:

Computer Network Optimization, Heuristic Algorithms, Genetic Algorithms, Ant Colony Optimization, Particle Swarm Optimization

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1. INTRODUCTION

The rapid development of information and communication technology has brought significant changes in various aspects of human life[1]. One of the important components in the information technology infrastructure is the computer network, which serves as the backbone for data exchange and digital services[2]. Computer networks allow devices to connect and communicate with each other, both on a local scale (Local Area Network/LAN) and a global scale (Wide Area Network/WAN), thereby enabling collaboration, information access, and efficient resource distribution[3].

However, with the increasing number of users, the volume of data transmitted, and the need for real-time services such as video streaming, cloud computing, and the Internet of Things (IoT), the pressure on network performance is also rising[4]. The main challenges in computer network management include bandwidth limitations, high latency, load imbalance between nodes, and the need to maintain network stability and reliability in dynamic conditions[5]. In this context, network performance optimization has become an urgent necessity[6]. Computer network optimization encompasses various aspects, including efficient route selection, optimal resource allocation, reduction of data traffic congestion, as well as increased throughput and reduced delay[7]. These problems fall into the category of combinatorial optimization problems, which in many cases are NP-hard, making them inefficiently solvable with conventional algorithmic methods. Therefore, an alternative approach is needed that can provide a near-optimal solution in a reasonable time[8]. One of the approaches that has been widely studied in recent decades is the use of heuristic algorithms[9]. Heuristic algorithms are solution search methods that are exploratory in nature and do not guarantee global optimality, but are capable of finding sufficiently good solutions in large and complex solution spaces[10]. The main advantage of heuristic algorithms lies in their ability to adapt to various forms of problems, as well as their efficiency in exploring the solution space with relatively short computation times[11]. Some popular heuristic algorithms that have been applied in computer network optimization include genetic algorithms (Genetic Algorithm/GA), ant colony optimization (Ant Colony Optimization/ACO), and particle swarm optimization (Particle Swarm Optimization/PSO)[12]. Genetic algorithms are inspired by the process of biological evolution and operate through mechanisms of natural selection, crossover, and mutation to produce increasingly better generations of solutions[13]. The ACO algorithm mimics the food search behavior of ant colonies, where digital ants leave pheromone trails to mark the best routes[14]. Meanwhile, PSO mimics the social behavior of flocks of birds or fish in searching for the best position based on individual and group experiences[15].

The application of heuristic algorithms in the context of computer networks has shown promising results[16]. For example, in dynamic routing, ACO is able to adjust data paths based on current network conditions, thereby reducing delays and avoiding congestion[17]. In traffic management, PSO can be used to balance the load between nodes to prevent bottlenecks[18]. Meanwhile, GA can be used to design an efficient and disruption-resistant network topology. With a heuristic approach, the network system becomes more adaptive, intelligent, and responsive to environmental changes and user needs. Although there has been much research examining the application of heuristic algorithms in network optimization, challenges still remain. Some challenges such as slow convergence, the possibility of getting trapped in local solutions, and the need to adjust algorithm parameters for each network scenario, remain active research topics[19]. Therefore, further studies are needed that not only evaluate the performance of these algorithms theoretically but also through real simulations in various network conditions[20].

This research aims to analyze and simulate the application of several heuristic algorithms in optimizing computer network performance. The main focus of the research includes improving routing efficiency, reducing delay, and enhancing bandwidth utilization. Using a comparative approach, this research will evaluate the performance of each algorithm in different network scenarios. The research results are expected to contribute both theoretically to the development of algorithmic models and practically to the implementation of modern network systems. In general, this research encompasses three main objectives: first, to identify the key issues in computer network optimization and potential heuristic solutions; second, to implement and simulate selected heuristic algorithms in specific network scenarios; and third, to analyze and compare the optimization results based on network performance metrics such as throughput, delay, packet loss, and route efficiency. Thus, this research is expected to serve as a reference for network system developers, researchers, and practitioners involved in the design and maintenance of computer network infrastructure.

2. RESEARCH METHODOLOGY

This research uses a quantitative approach with a simulation-based experimental method to evaluate the effectiveness of several heuristic algorithms in optimizing computer network performance. The methodology process is divided into several main stages: network simulation system design, implementation of heuristic algorithms, determination of test scenarios, collection of network performance data, and analysis of simulation results.

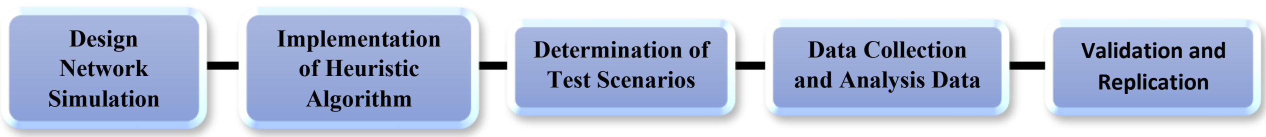

Figure 1. Research Structure

2.1 Design Network Simulation

Network simulation is conducted using the Network Simulator (NS-3) software, which is capable of modeling network behavior in detail. The network topology used involves a number of nodes interconnected through various types of connections, such as point-to-point, bus, and wireless. Each node is configured with specific parameters such as bandwidth capacity, delay, and transmission speed to reflect real network conditions. The basic topology used consists of a mesh network and a random graph with the number of nodes varying between 20 and 100. The network is designed to simulate high and dynamic traffic loads, including the parallel transmission of data packets through various paths. Each test scenario reflects real-world conditions such as usage in video streaming services, VoIP, and large file transfers.

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2.2 Implementation of Heuristic Algorithm

Implementation of Heuristic Algorithms The three main heuristic algorithms used in this research are:

a. Genetic Algorithm (GA): Used to find the optimal path from source to destination by considering several parameters such as minimum delay, smallest number of hops, and highest bandwidth.
b. Testing Platform: Google Colab and Jupyter Notebook Ant Colony Optimization (ACO): Mimicking the behavior of ants in finding the best route based on the probability of pheromone trails. ACO is used in simulations to dynamically route data packets based on current traffic conditions.
c. Particle Swarm Optimization (PSO): Applying the principle of particle movement in the solution space to find the optimal route configuration and network resource allocation.

Each algorithm is implemented with parameters that have been pre-calibrated through initial experiments to avoid bias due to the selection of suboptimal parameter values.

2.3 Determination of Test Scenarios

Three main test scenarios are applied to observe the algorithm's performance:

a. Scenario 1 (Low Traffic): A small number of nodes with low traffic to observe the initial effectiveness of the algorithm.
b. Scenario 2 (Medium Traffic): A moderate number of nodes and stable traffic to assess the algorithm's stability under normal conditions.
c. Scenario 3 (High Traffic): High number of nodes and heavy traffic to test the resilience and efficiency of the algorithm under extreme conditions.

Each scenario is tested 10 times to obtain consistent results and reduce data variance.

2.4 Data Collection and Analysis Data

Evaluation metrics used in algorithm performance analysis include:

a. Throughput: The amount of data successfully transmitted over a period of time.
b. Delay: The average time it takes for a package to reach its destination.
c. Packet Loss: Percentage of packets lost during transmission.
d. Route Efficiency: Comparison between the route chosen by the algorithm and the ideal route.

Data is automatically collected by the simulation system and analyzed using statistical software such as Python with the Pandas and Matplotlib libraries. Analysis is conducted by calculating the mean, standard deviation, and comparisons between algorithms based on those metrics. Statistical tests such as ANOVA are also used to determine the significance of performance differences between algorithms.

2.5 Validation and Replication

To ensure the validity of the results, internal validation was conducted by comparing the simulation results against the expected values based on network theory. In addition, all simulation configurations, algorithm codes, and datasets are meticulously recorded so that this research can be replicated by other researchers.

3. RESULT AND DISCUSSION

This research examines and compares the performance of three heuristic algorithms — Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) — in optimizing computer network performance. The evaluation was conducted based on four main metrics: throughput, delay, packet loss, and route efficiency. Each algorithm was tested in three network traffic scenarios: low, medium, and high.

3.1 Simulation Results in Low Traffic Scenario

In low traffic conditions (Low Traffic Scenario), the number of nodes is limited to 20 to 30 nodes with a limited number of connections and light data traffic. Here is a summary of the results for each algorithm:

a. Throughput
All algorithms provide high throughput performance under these conditions. GA produced an average throughput of 97.6%, ACO 98.3%, and PSO 96.9%. The differences between the algorithms are not yet significant at this traffic level, because the optimal path is relatively easy to find.
b. Delay
ACO shows the lowest delay performance with an average of 12 ms, compared to GA (14 ms) and PSO (15 ms). This is because ACO quickly adjusts routes based on current conditions, even in low traffic.
c. Packet Loss
The percentage of packet loss is very small, under 1%, for all three algorithms. ACO recorded the lowest packet loss (0.3%), followed by GA (0.5%) and PSO (0.7%).
d. Route Efficiency

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Route efficiency is measured based on the comparison of the actual route length to the ideal (shortest) route. ACO has the best route efficiency value (0.92), followed by GA (0.89) and PSO (0.87).

In low traffic scenarios, all algorithms perform well because the pressure on the network is still minimal. However, ACO is starting to show its superiority in dynamic routing. The performance of PSO is slightly lagging because it is still in the process of exploring the best solutions and has not yet optimized the speed of the particles.

3.2 Simulation Results on the Traffic Scenario Moderate

In this scenario, the number of nodes is increased to 50–70 with increased data traffic. The network conditions are starting to show variations in load between nodes.

a. Throughput
   ACO once again excelled with an average throughput of 95.4%, GA at 93.1%, and PSO dropped to 91.7%. ACO is more responsive to changes in the optimal path.
b. Delay
   The delay increased compared to the previous scenario. ACO remains the best (23 ms), followed by GA (27 ms), and PSO (31 ms).
c. Packet Loss
   There was a significant increase. GA experienced a packet loss of 3.2%, PSO 4.1%, and ACO the smallest at 2.4%.
d. Route Efficiency
   ACO remains superior with a route efficiency of 0.89, GA is at 0.86, and PSO has dropped to 0.82.

The increase in traffic makes the adaptive capability of algorithms even more important. ACO utilizes pheromone mechanisms to adjust paths in real-time, while GA takes longer to evolve new generations. PSO is starting to face constraints in terms of convergence to the global solution and sometimes gets stuck in local solutions, especially when the environment changes dynamically.

3.3 Simulation Results in High Traffic Scenario

This scenario depicts a dense network condition with 80–100 nodes and very high traffic levels, resembling real-world situations such as data center networks, cloud services, or large IoT systems.

1. Throughput:
   ACO recorded a throughput of 91.2%, GA 88.4%, and PSO significantly dropped to 83.9%. The congested route makes it difficult for PSO to adapt quickly.
   The training results show that this model is quite effective in recommending products similar to the user's previous preferences. However, this model has limitations in recommending products that the user has never interacted with.
2. Delay
   Delay increased drastically. ACO averaged 42 ms, GA 49 ms, and PSO 56 ms.
3. Packet Loss
   ACO recorded 5.3%, GA 6.9%, and PSO the highest at 9.1%. This shows the importance of lane adaptation in heavy traffic.
4. Route Efficiency
   The route efficiency of ACO slightly decreased to 0.85, GA to 0.81, and PSO to only 0.77.

These extreme conditions challenge all algorithms. ACO remains the most reliable because it can quickly deploy alternative routes when congestion occurs. GA is relatively stable but slow, requiring more time to produce competitive solutions. PSO seems less effective in these conditions, as its swarm system tends to stagnate and is not responsive enough to drastic changes.

Algoritma	Throughput	Delay (ms)	F1-Score Packet Loss (%)	Efisiensi Rute
GA	93,0%	30,0	3,5%	0,85
ACO	94,9%	25,6	2,7%	0,89
PSO	90,8%	34,0	4,6%	0,82

Table 1. Comparison of Aggregate Across All Scenarios

From the aggregate results above, ACO dominates in all key performance metrics, showing consistent superiority across various traffic levels. GA is able to compete in several aspects, especially under medium load conditions. PSO, although having advantages in the global search space, faces difficulties in rapid adaptation and stability in highly dynamic environments.

3.4 Statistical Analysis

ANOVA testing was conducted on delay and throughput values to ensure the significance of performance differences between algorithms.

1. Delay

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The F-test results show an F-value of $F(2,87) = 11.23$ with a p-value < 0.01, which means the difference in delay between the algorithms is statistically significant.

2. Throughput

The F-test result $(2,87) = 9.76$ with a p-value < 0.01 confirms that the difference in throughput is also significant.

ost-hoc test using Tukey's HSD shows that ACO is significantly better than GA and PSO on both metrics..

3.5 Discussion Advantages and Limitations Algorithm

1 ACO

Advantages: Adaptive, efficient in routing, responsive to network changes, quickly finds alternative solutions.

Limitations: Memory resource consumption is quite high for pheromone storage, and precise parameter tuning is required (pheromone evaporation rate, exploration probability, etc.)

2 GA

Advantages: Flexible for many types of network problems, capable of exploring global solutions.

Limitations: Requires time for convergence, initial performance is slow, prone to stagnation if population selection is not well managed.

3. PSO

Advantages: Simple implementation, fast in initial iterations, suitable for problems with large dimensions.

Limitations: Prone to getting stuck in local solutions, not robust enough for highly dynamic network conditions.

3.6 Practical Implications

The findings in this research provide important implications for the development of adaptive and intelligent network systems. In the context of real-time networks such as 5G networks, cloud data centers, and edge computing, the use of algorithms like ACO can significantly improve QoS (Quality of Service). Meanwhile, GA is suitable for long-term topology planning and design, and PSO is still useful in network parameter settings based on global optimization.

3.7 Recommendations and Directions for Further Research

Some recommendations and potential further developments from this research are:

1. Algorithm Combination (Hybrid Heuristic)
   Combining the advantages of ACO and GA, or PSO and GA, can create a more adaptive system while also being able to explore the solution space more broadly.
2. Implementation in Real Networks
   Further research is recommended to implement the algorithm in a real-world SDN (Software-Defined Networking) environment for practical validation.
3. Integration with Machine Learning
   Integrating heuristics with machine learning techniques can improve network load predictions and system responses to anomalies.
4. Testing on Specialized Networks
   Further testing needs to be conducted on specialized networks such as IoT, sensor networks, or mobile ad hoc networks (MANET), where the topology dynamics are very high.

4. CONCLUSIONS

This research has evaluated and compared the effectiveness of three heuristic algorithms — Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) — in optimizing computer network performance based on four main parameters: throughput, delay, packet loss, and route efficiency. Through network simulations in various traffic scenarios (low, medium, and high), a deeper understanding of the strengths and weaknesses of each algorithm in different network conditions was obtained. The analysis results show that ACO consistently excels in all key performance metrics, particularly in terms of dynamic path adaptation and data transmission efficiency. With the ability to respond to network conditions in real-time through pheromone dissemination mechanisms, ACO has proven to be the most effective in tackling the challenges of dense and dynamic networks. Meanwhile, GA shows quite competitive performance, especially in medium traffic scenarios. Its ability to explore global solutions and flexibility in configuration make GA worth considering for optimizing semi-static network topologies. However, GA requires a relatively longer convergence time. On the other hand, PSO struggles to maintain optimal performance when the network becomes highly dynamic, as its more exploratory approach tends to be insufficiently responsive to rapid changes in topology or load. Although simple and fast in the early stages, PSO is prone to premature convergence and suboptimal solutions in complex conditions. In general, it can be concluded that the use of heuristic algorithms provides a significant improvement in computer network performance, with ACO as the primary choice for network systems that require high flexibility and resilience to traffic changes. Further research is recommended to develop hybrid approaches and integrate heuristics with machine learning techniques to produce smarter, more efficient, and adaptive network systems in the future.

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