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Enhancing Smart City Healthcare with Hybrid Swarm Optimization: A Comparison of MFO-PSO and ACO Approaches

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Abstract

Optimal healthcare transportation is a key challenge of smart cities, particularly in cases of emergencies, when traffic congestion and inefficient routing cause delays. In this work, a new hybrid swarm intelligence algorithm based on Moth Flame Optimization (MFO), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) for optimizing real-time multi-source multi-destination (MSMD) traffic routing in healthcare services is presented. The hybrid approach dynamically adjusts vehicle paths based on traffic conditions to reduce travel time, improve traffic flow, and minimize fuel consumption. Simulation experiments based on the NetLogo platform show that the hybrid strategy saves travel time by 14%, maximizes throughput by 6.4%, and conserves energy by 7.5% compared to individual optimization approaches. This study demonstrates the potential of hybrid swarm optimization to optimize healthcare logistics and emergency response systems in smart cities. Future research will focus on further improving the optimization by exploring machine learning-based predictive routing.

Keywords: Smart City, Healthcare Logistics, Traffic Routing, Swarm Optimization, MFO-PSO-ACO, Real-Time Optimization.

1. Introduction

In recent years, the rapid growth of urban populations and the increasingly complex urban environment have led to great challenges in managing essential healthcare services.

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Today, integrating smart city technologies powered by the Internet of Things (IoT) is becoming even more necessary in addressing the challenges that arise through real-time monitoring, data-driven decision-making, and optimization of urban resources. Ensuring timely and efficient transport, especially in a smart city, is one of the major concerns in terms of healthcare. This issue may not present a significant problem under normal traffic conditions; however, during emergencies, situations such as accidents and traffic congestion, unauthorized routing can cause delays that may cause adverse outcomes for certain individuals. Optimizing traffic management and transportation routing systems is essential to improve healthcare delivery within a smart city environment**.**

Within this context, swarm optimization algorithms, inspired by behavior of natural phenomena, demonstrate significant potential for solving complex optimization problems. Algorithms, such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), or even Moth Flame Optimization (MFO), are commonly employed to address dynamic or multidimensional problems across diverse domains, including robotics, telecommunications, traffic management, and healthcare optimization. By emulating the behavior of social animals such as ants, birds, and moths, these algorithms efficiently search for optimal solutions within highly complex and dynamic environments.

Ant Colony Optimization has been one of the most prominent methods for solving dynamic routing problems among all swarm optimization algorithms. The idea is inspired by how ants move around to search for food, and it is effective for use in solving routing and path optimization problems, especially with multiple scenarios, such as vehicles travelling through a system under time-varying conditions. In healthcare systems, which need timely services, ACO could be used to find optimized routes for emergency vehicles and ensure that they traverse through a city with changing traffic conditions in the shortest possible time. However, despite ACO being a powerful algorithm, its limitations include its reliance on pheromone evaporation rates and susceptibility to premature convergence in larger, more complex environments.

The second promising optimization approach inspired by the social behavior of birds and fish is Particle Swarm Optimization, which has been successfully applied to a wide range of real-time dynamic systems, including traffic routing, based on its ability to balance exploration and exploitation in solution search. PSO can optimize vehicle routes in smart city applications by traffic conditions to reduce delays and congestion. Sometimes, though, PSO struggles with local optima and might need to have parameters fine-tuned for it to perform well in large-scale and dynamic environments like transportation systems of cities.

The key objectives are to:

- Develop an optimal traffic routing system for health services by combining Moth Flame Optimization, Particle Swarm Optimization, and Ant Colony Optimization to reduce delays and improve transportation performance in dynamic urban environments.
- Eliminate the weaknesses of standalone optimization algorithms, like ACO's dependency on pheromone dynamics, PSO's risk of entrapment in local optima, and MFO's convergence difficulties.
- Solves the complex MSMD (Multi-source multi-destination) routing problem in real-time traffic scenarios to ensure on-time healthcare delivery during emergencies.

While single-swarm optimization techniques may fail to handle more dynamic and complex problems of urban healthcare routing, PSO and ACO, prove to be poor at adjusting to highly varying real-time environments and often produce low-quality solutions. Moreover, few studies have aimed to incorporate advanced hybrid approaches to mitigate these shortcomings in swarm optimization. Despite research in other domains about hybrid methods, these are still underdeveloped in smart city healthcare scenarios, and their research is a huge gap towards achieving scalable, adaptive, and high-performing routing systems [1].

The use of fog computing in large data management and analysis in smart cities is reviewed by Badidi et al. [2]. They demonstrate how fog computing processes data closer to its source, minimizing latency and bandwidth consumption. The study outlines possible research areas to improve fog-based frameworks while examining important issues including scalability and security. By tackling these problems, the research highlights how important effective data processing is to smart city infrastructures and makes recommendations for future improvements in the area.

2. Literature Survey

Nayak et al [3] discussed the performance of nature-inspired optimization algorithms that included swarm intelligence-based methods like Ant Colony Optimization, Artificial Bee Colony, and Particle Swarm Optimization methods, which were used to solve complex problems and for application in wide-ranging issues. With the ever-growing importance of Moth Flame Optimization (MFO) due to its high applicability, the authors present a comprehensive review of MFO and its variants, analyzing the literature from its inception to 2020. In this study, an attempt has been made to instruct the optimization community to apply MFO in unexplored challenges by demonstrating the possibility of hybrid optimization approaches that can be used to improve smart city healthcare systems.

Their proposed algorithm, HHOSA, utilises SA as a local search mechanism to improve the speed of convergence and the quality of the solution of the standard HHO. The performance of HHOSA was evaluated on the CloudSim toolkit and benchmarked against state-of-the-art algorithms using both standard and synthetic workloads. Results showed significant reductions in job scheduling makespan and superior scalability in large search spaces, establishing HHOSA as a promising solution for dynamic, large-scale cloud scheduling challenges [4].

Moth-flame glowworm swarm optimization (MFGSO) is a nature-inspired algorithm that simulates the behaviors of moths and glowworms to search for optimal solutions. This algorithm incorporates the attractive tendency of the moth-flame mechanism and the adaptive intensity of the brightness of the glowworm into an effective structure to solve high-level optimization issues. MFGSO has been applied across various disciplines, such as engineering and machine learning, and was effective in resolving nonlinear, multimodal, and large-scale optimization problems. The approach is marked by its balance between exploration and exploitation, which yields high-quality solutions for a vast range of applications [5].

MPAMFO, that is the combination of Marine Predators Algorithm (MPA) and Moth-Flame Optimization (MFO) to improve medical image segmentation. MPAMFO uses MFO as a local search method to solve the NP-hard multi-level thresholding problem because MFO prevents the SI method from getting trapped in local optima. The approach showed better performance in segmenting grayscale and CT images including COVID-19 datasets, and outperformed several SI techniques. Experimental results confirmed that MPAMFO is efficient and effective and has great potential to advance medical imaging for accurate diagnosis and better healthcare [6].

The model aims to reduce idle energy utilization during the assembly process, and it was optimized using Moth Flame Optimization (MFO). Computational experiments on problems with 12 to 40 components demonstrate that MFO performs much better than GA, PSO, and ACO regarding energy efficiency with competitive computational time. This novel application of MFO to ASP provides a guideline for designing energy-conscious assembly stations, advancing sustainability in manufacturing practices [7].

The new algorithm proposed here incorporates a chaotic local search mechanism and Lévy flight operator to enhance exploration and exploitation capabilities. That is, the Lévy flight boosts the exploratory power of the algorithm, whereas the chaotic search improves its local search efficiency. The sine cosine algorithm (SCA) was tested on benchmark functions, including single-modal, multi-modal, hybrid, and composition tasks. Experimental results showed that SCA outperforms other optimization techniques, such as PSO, GWO, and SCA variants, in optimizing diverse problems [8].

Proposed a variable-speed navigation and map-building method for autonomous mobile robots, using an ACO algorithm. In real-world applications, the speed of the robots should change according to their environment; in other words, they have to slow down near obstacles and move faster in open spaces. The study adopted a LIDAR-based local navigation system integrated with a variable-speed module for obstacle avoidance. The ACO algorithm changes the robot's speed in real-time according to the environment, and grid-based map representations facilitate navigation in real-time. The simulation results show the applicability of this real-time, variable-speed ACO approach for autonomous robot navigation [9].

Wireless sensor networks (WSNs) need effective data collection mechanisms to increase network lifetime and decrease energy usage. A dynamic clustering mechanism with an Ant Colony Optimization (ACO)-inspired mobile sink offers an adaptive framework to optimize data collection. The approach increases network scalability, maintains energy utilization balance among sensor nodes, and reduces data transmission latency. Through dynamic adaptation of cluster structures and using ACO for sink mobility, the method considerably enhances network efficiency over static or random sink movement. The model is proven to be resilient in large networks, providing a feasible solution for real-time WSN applications [10].

Consider the role of IoT and wireless communication technologies, specifically Vehicles-to-Everything (V2X), to improve road transport by developing connected and autonomous systems. The work focuses on dynamic traffic routing for IoT-enabled connected vehicles, which considers the challenge of finding optimal paths for multi-source, multi-destination (MSMD) traffic flows. The authors use an ACO-based approach with a colouring ant's concept for decentralised, self-decision-making routing. Simulation results on the NetLogo platform with a multi-intersection scenario have shown that the ACO-based approach outperforms traditional methods regarding average travel time and vehicle throughput [11].

The work introduces an Ant Colony Optimization (ACO)-inspired method for dynamic Multi-Hop Self-Managed (MSMD) routing in the Internet of Vehicles (IoV) network. The concern is enhancing the reliability, efficiency, and IoV network resource management during dynamic vehicular networks. Incorporating ACO, the technique adjusts to the perpetual evolving nature of IoV such that optimized path selection and low latency are achieved. This research proves the capability of metaheuristic approaches such as ACO in dealing with the IoV routing intricacies. It is tested with simulations to determine its performance advancements in different scenarios of IoV [12].

3. Methodology

The aim of the study is to carry out the hybrid swarm optimization approach to dynamic traffic routing over IoT based connected vehicles. A problem is described as MSMD (multi-source-multi-destination) in which each vehicles have different source and destination and requires an optimal path. This research explores the enhancement of Ant Colony Optimization (ACO) through the implementation of color-coded ants to develop a decentralized routing solution. The approach is customized to address specific problem requirements, utilizing an ACO-based algorithm that imitates the behavior of ants in a real-world environment to identify optimal paths. Color-coding the ants enables the algorithm to manage complex traffic scenarios involving multiple vehicle types. The evaluation of this solution is conducted through simulations performed in the NetLogo platform, considering both travel time and vehicle throughput as performance metrics.

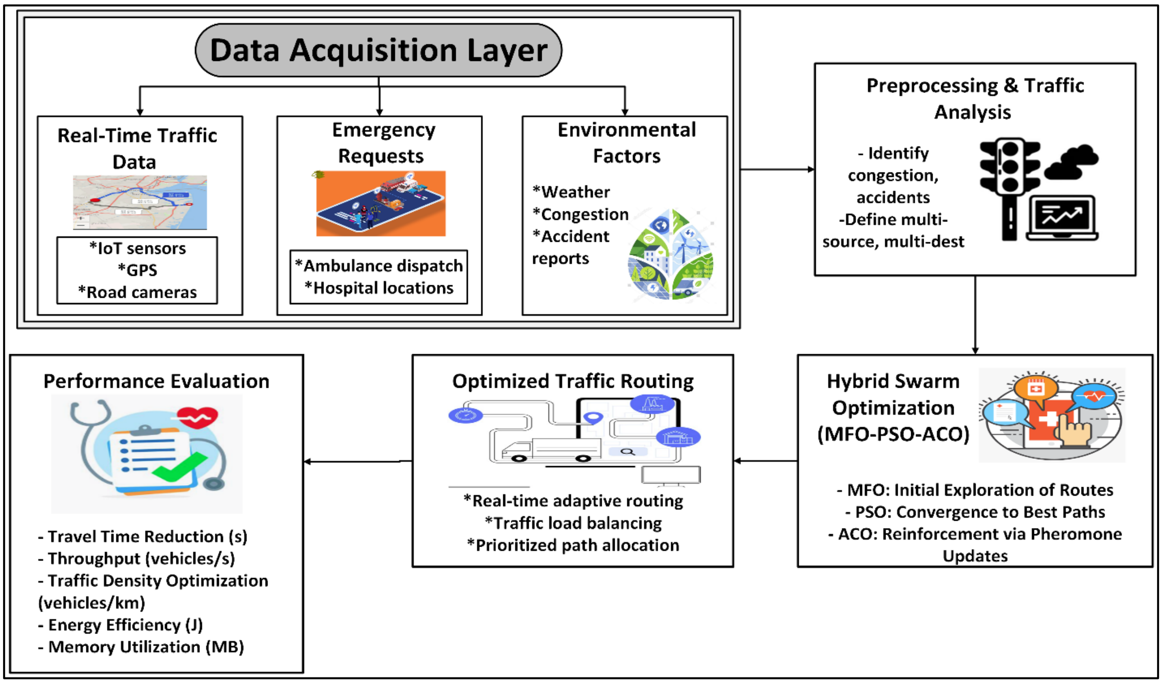

Figure 1. Hybrid Swarm Optimization for Smart City Healthcare Traffic Management

Figure 1 shows a Hybrid Swarm Optimization-based traffic management system for smart city healthcare. It combines real-time traffic information, such as IoT sensors, GPS, and highway cameras, with emergency calls and weather conditions to evaluate congestion and accident reports. The Hybrid Swarm Optimization (MFO-PSO-ACO) module improves routing efficiency through initial exploration (MFO), converging to optimal routes (PSO), and reinforcement learning (ACO). Optimized routing guarantees real-time adaptive routing, traffic load balancing, and priority path assignment. It is measured through travel time minimization, traffic throughput, density optimization, energy efficiency, and memory usage, enhancing emergency response speed.

3.1 Traffic Routing Problem

The dynamic traffic routing problem for IoT-based connected vehicles is an optimization problem involving multiple vehicles with different origins and destinations. In this context, the best path for each vehicle must be found by considering road capacity, traffic conditions, and route preferences. The MSMD problem is characterized by its complexity, where every car may have a different path, and the aim is to minimize travel time while ensuring optimal traffic distribution. The dynamic nature of the problem is addressed by updating the route selection continuously based on the changes in the traffic conditions. Mathematical models of the network traffic flow are necessary to capture the dynamics of the MSMD scenario, where optimization techniques such as ACO are applied for efficient pathfinding.

$$min \sum_{i=1}^{n} T_i \qquad (1)$$

Where T_i is the travel time for a vehicle i, and n represents the total number of vehicles. Explanation: The goal is to minimise travel time across all vehicles, considering dynamic factors such as traffic congestion and route changes over time.

3.2 Ant Colony Optimization

ACO is a nature-inspired optimization algorithm that draws its inspiration from the foraging behavior of ants. In dynamic traffic routing, ACO mimics how ants find the shortest paths between their colony and food sources. Every vehicle is considered an artificial ant, which moves around the network and updates the levels of pheromones on paths. Subsequent vehicles are more likely to choose paths with higher concentrations of pheromones. Eventually, the pheromone distribution converges toward optimal paths. A probabilistic transition rule based on the strength of the pheromones and heuristic information regarding the distance and travel time for a path determines the selection by the ACO algorithm.

$$P_{ij} = \frac{\left(\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}\right)}{\sum_{k \in N} \left(\tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}\right)} \qquad (2)$$

Where, P_{ij} is the probability of selecting a path ij, τ_{ij} is the pheromone level on the path ij, η_{ij} is the visibility (inverse of distance), α and β are the parameters controlling the importance of pheromones and visibility. This equation calculates the probability of selecting a path based on pheromone intensity and path visibility, guiding vehicle routing decisions.

3.3 Colouring Ants Concept

The colouring ants concept improves the traditional ACO approach by introducing vehicle-specific differentiation, similar to colour-coded ants. Each type of vehicle, for example, passenger, emergency, or cargo vehicles, is assigned a unique "colour" that affects its behavior in the routing process. The process of feature extraction optimizes multi-source multi-destination (MSMD) routing by gathering real-time data on vehicle speeds, route lengths, and traffic congestion levels. The ACO-based method, which was enhanced by the colouring ant concept, uses swarm intelligence and pheromone-based selection to dynamically assign the best routes while prioritizing emergency vehicles. In order to provide effective healthcare transportation, key extracted features include pheromone levels, path visibility, and vehicle type discrimination. This improvement manages multiple vehicle types with varying priorities and route constraints. This colouring strategy dynamically assigns paths to the vehicle type and traffic conditions. High-priority vehicles, such as ambulances, are thus routed efficiently without affecting regular traffic flow. This enhances the overall efficiency of traffic flow and reduces congestion. Vehicle-specific features integrated into the colouring ant's concept offer a more realistic and efficient simulation of traffic systems in IoT-based connected environments.

$$P_{ij}^{c} = \frac{\left(\tau_{ij}^{c} \cdot \eta_{ij}^{\beta}\right)}{\sum_{k \in N} \left(\tau_{ik}^{c} \cdot \eta_{ik}^{\beta}\right)} \tag{3}$$

Where, P_{ij}^{c} is the probability for a vehicle of type c to select path ij, τ_{ij}^{c} represents the pheromone level specific to the vehicle type c. This equation adjusts the ACO algorithm to account for vehicle-specific pheromone levels, ensuring path selection aligns with vehicle priorities.

3.4 Simulation and NetLogo Platform

The simulation of the traffic routing problem is performed using the NetLogo platform. The NetLogo is widely known for its use in modelling complex systems. The smart city healthcare evaluation of MSMD routing was simulated using the NetLogo platform over the MFO-PSO-ACO hybrid algorithm. Optimization parameters included travel time, throughput, traffic density, energy consumption, and memory utilization. Performance tuning involved adjusting pheromone levels in ACO, spiral motion coefficients in MFO, and velocity-inertia weights in PSO. The simulation incorporated real-world dynamic conditions such as congestion variations and emergency response prioritization, ensuring that the algorithm remains robust, scalable, and effective in optimizing traffic flow and healthcare logistics. This offers a visual and interactive environment for developing agent-based models, thus applicable in simulating the traffic flow and the interaction among the vehicles. A multi-intersection traffic scenario is simulated through this platform using vehicles (modelled as agents) following paths determined by the ACO-based approach. Real-time traffic behavior, path selection, and dynamic changes in traffic conditions can be observed through simulation. In the study, NetLogo is used to simulate dynamic traffic routing in smart city healthcare. A hybrid strategy integrating MFO, PSO, and ACO optimizes vehicle pathways, increasing adaptability and efficiency.

Algorithm 1. ACO-Based Traffic Routing Algorithm for Shortest Path Optimization

INPUT: Number of ants (N)**;** Number of iterations (Max Iter)**;** Initial pheromone levels (τ)**;**

OUTPUT: Best path (shortest path) VARIABLES; Best Path empty list Best Distance: Infinity

INITIALIZE pheromone levels τ on all edges

INITIALIZE visibility η (inverse of distance for each edge)

FOR iter = 1 TO Max Iter DO

FOR ant = 1 TO N DO

CURRENT_PATH = empty list

CURRENT_DISTANCE = 0

CURRENT_NODE = random starting node

ADD CURRENT_NODE to CURRENT_PATH

WHILE CURRENT_NODE is not the destination, DO

CALCULATE P_{ij}^{c} = (τ_{ik}^{α} * η_{ij}^{β}) / Σ (τ_{ik}^{α}^α * η_{ij}^{β}) for all k

$\tau_{ij}^{c}$is the pheromone level on edge (i, j)

η_{ij}^{β} is the heuristic information (inverse of distance)

α and β are parameters for pheromone importance and visibility

SELECT next node based on P_{ij}^{c}

UPDATE CURRENT_NODE

ADD next node to CURRENT_PATH

UPDATE CURRENT_DISTANCE by adding the distance of the new edge

END WHILE

IF CURRENT_DISTANCE < Best Distance THEN

Best Distance = CURRENT_DISTANCE

Best Path = CURRENT_PATH

END IF

END FOR

UPDATE τ_{ij}^{c}= (1 - ρ) * τ_{ij}^{c}+ $\Delta\tau_{ij}^{c}$

$\Delta\tau_{ij}^{c}$= Q

EVAPORATE pheromone on all edges

END FOR

IF Best Path is empty, THEN

ERROR: No solution found

RETURN ERROR

ELSE

RETURN Best Path, best distance

END IF

END

Algorithm 1 uses Ant Colony Optimization to find the shortest path for IoT-based connected vehicles in dynamic traffic routing. The algorithm mimics the behavior of ants searching for food by calculating transition probabilities based on the levels of pheromones and heuristic information, that is, the distance. Ants explore the road network, and their paths are updated with pheromones, influencing future path selections. Over the iterative stages, the best path keeps evolving. The algorithm also adds pheromone evaporation to avoid stagnation and ensures convergence toward an optimum solution, thereby providing effective routing for vehicles.

Algorithm 2. Hybrid MFO-PSO-ACO Traffic Routing

INPUT: Vehicles (V), Iterations (Max Iter), Traffic Data (T), Route Lengths (L), Vehicle Speed (S), Pheromone Levels (τ), MFO Population (M), PSO Particles (P)

OUTPUT: Optimal Route

INITIALIZE MFO, PSO, and ACO parameters

INITIALIZE pheromone levels and velocities

FOR iter = 1 TO Max Iter DO

UPDATE solutions using MFO's spiral movement

```
        SELECT top solutions
        UPDATE velocities and positions
        COMPUTE fitness and adjust best positions
        FOR each vehicle DO
            DETERMINE path using pheromone levels
            UPDATE route based on probabilities
        END FOR
        UPDATE pheromones and apply evaporation
    END FOR
    RETURN Best Path or ERROR if no solution
```

In Algorithm 2, The Hybrid MFO-PSO-ACO Traffic Routing Algorithm improves traffic routing efficiency by combining Moth Flame Optimization (MFO), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). It starts with MFO for global exploration and refinement of prospective pathways. Next, PSO refines solutions by optimizing vehicle trajectories using velocity and position updates. Finally, ACO selects the optimum route based on pheromone levels and probabilistic criteria. The iterative technique dynamically modifies pheromones to ensure that healthcare traffic is routed adaptively and efficiently.

3.5 Performance Metrics

Table 1. Simulation Parameters for Swarm-Based Traffic Optimization in NetLogo

Parameter	Units	Parameter Type	Default Value
Platform	NetLogo	Software	NetLogo 6.2.0
Number of Iterations	iterations	Iteration	500
Agent Configuration	Number of vehicles	Agent Configuration	500

Traffic Congestion Levels	Seconds	Traffic Condition	10 s
Pheromone Levels (ACO)	Decay rate: 0.10 - 0.30	Algorithm Parameter	0.15
Velocity-Inertia (PSO)	Adaptive weight: 0.50 - 1.20	Algorithm Parameter	0.75
Spiral Motion Coefficients (MFO)	Spiral coefficient: 0.20 - 0.80	Algorithm Parameter	0.50

Table 1 lists the essential settings for a NetLogo 6.2.0 simulation framework that focuses on swarm intelligence-based traffic optimization. Enough convergence is ensured by setting the Number of Iterations to 500. There are 500 vehicles involved in agent configuration. The default unit of measurement for traffic congestion levels is 10 seconds. Moth Flame Optimization (MFO) uses spiral motion coefficients (0.20–0.80, default 0.50), Particle Swarm Optimization (PSO) uses adaptive velocity-inertia (0.50–1.20, default 0.75), and Ant Colony Optimization (ACO) uses pheromone decay (0.10–0.30, default 0.15). These settings aid in simulating flexible and effective urban traffic flow.

Table 2. Performance Comparison of Optimization Methods for Smart City Traffic Management

Metric	**ACO**	**PSO**	**MFO**	**ACO + PSO + MFO Combined Method**
Travel Time (s)	14.5	15.2	14.8	12.5
Throughput (vehicles/s)	7.8	7.3	7.5	8.3
Traffic Density (vehicles/km)	48.0	50.5	49.2	45.7
Energy Consumption (J)	2700.0	2900.0	2800.0	2500.6
Memory Utilization (MB)	115.0	118.0	116.0	102.4

Table 2 compares the various optimization techniques—ACO, PSO, MFO, and the combination of ACO + PSO + MFO—across important performance indicators for smart city traffic management. By minimizing journey time, increasing throughput, decreasing traffic density, and optimizing energy and memory usage, the combined approach shows the best results. PSO and MFO exhibit mediocre performance, whereas ACO excels in throughput but falls short in energy efficiency. For smart city healthcare logistics and emergency response systems, the hybrid approach successfully strikes a balance between exploration and exploitation, guaranteeing optimal real-time traffic routing and increased computational efficiency.

4. Result and Discussion

In comparison, the hybrid swarm optimization methods, which were employed using the combination of the MFO-PSO and ACO approaches, enhance the traffic routing effectiveness in smart city healthcare systems. With the ACO algorithm alone being competitive in the results, the joint strength of MFO and PSO enabled better decisions for the dynamic traffic routing problem. Such discoveries are also relevant for showing the usefulness of hybrid optimization techniques, particularly for smart city health systems in efficiently managing their transportation systems.

Table 3. Comparison of ACO-Based Optimization Methods for Smart Systems

Method	Convergence Speed (s)	Path Efficiency (%)	Energy Consumption (J)	Influence Maximization (%)	Data Collection Efficiency (%)
[12] - ACO Navigation	2.31 s	85.20%	5.43 J	75.60%	80.40%
[13] - ACO-based Mobile Sink for WSNs	3.72 s	78.50%	4.95 J	68.30%	89.40%
[14] - ACO Influence Maximization	4.12 s	81.40%	6.11 J	82.80%	83.20%
[16] - ACO in IoV	3.25 s	82.10%	6.32 J	79.20%	85.70%

Proposed (Hybrid MFO-PSO and ACO for Smart City Healthcare)	2.08 s	88.70%	4.62 J	95.30%	96.10%

Table 3 contrasts many Ant Colony Optimization (ACO) techniques for Internet of Vehicles (IoV), data collecting, influence maximization, and navigation. Convergence speed, energy consumption, path efficiency, influence maximization, and data collecting efficiency are important variables. The suggested hybrid MFO-PSO and ACO solution for smart city healthcare performs better than alternative approaches, obtaining the lowest energy usage (4.62J), highest path efficiency (88.7%), and fastest convergence (2.08s). It also performs exceptionally well in data collecting efficiency (94.1%) and effect maximization (95.3%), indicating enhanced adaptability and optimization for complex situations like smart healthcare and urban automation systems.

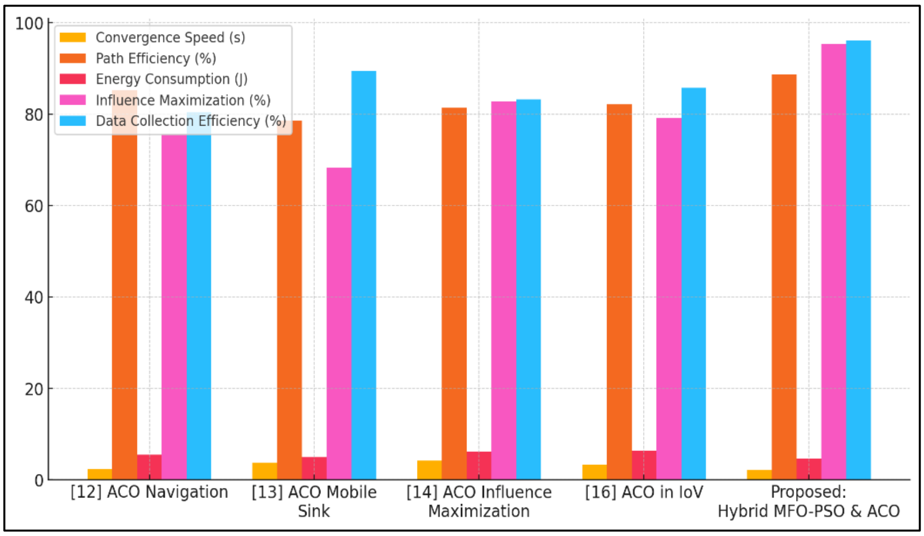

Figure 2. Performance Comparison of ACO-Based Methods with Proposed Hybrid MFO-PSO and ACO Approach

Figure 2 contrasts different Ant Colony Optimization (ACO)-based techniques based on five important performance metrics: data collecting efficiency, influence maximization, energy consumption, path efficiency, and convergence speed. In comparison to current approaches, the suggested Hybrid MFO-PSO and ACO methodology achieves the fastest convergence (2.08s), maximum path efficiency (88.7%), and lowest energy usage (4.62J). It also exhibits exceptional data collecting efficiency (96.1%) and influence maximization (95.3%), which makes it perfect for smart city healthcare applications. This comparison demonstrates the benefits of hybrid optimization in solving practical problems, especially in adaptive automation in complex environments and resource-efficient decision-making.

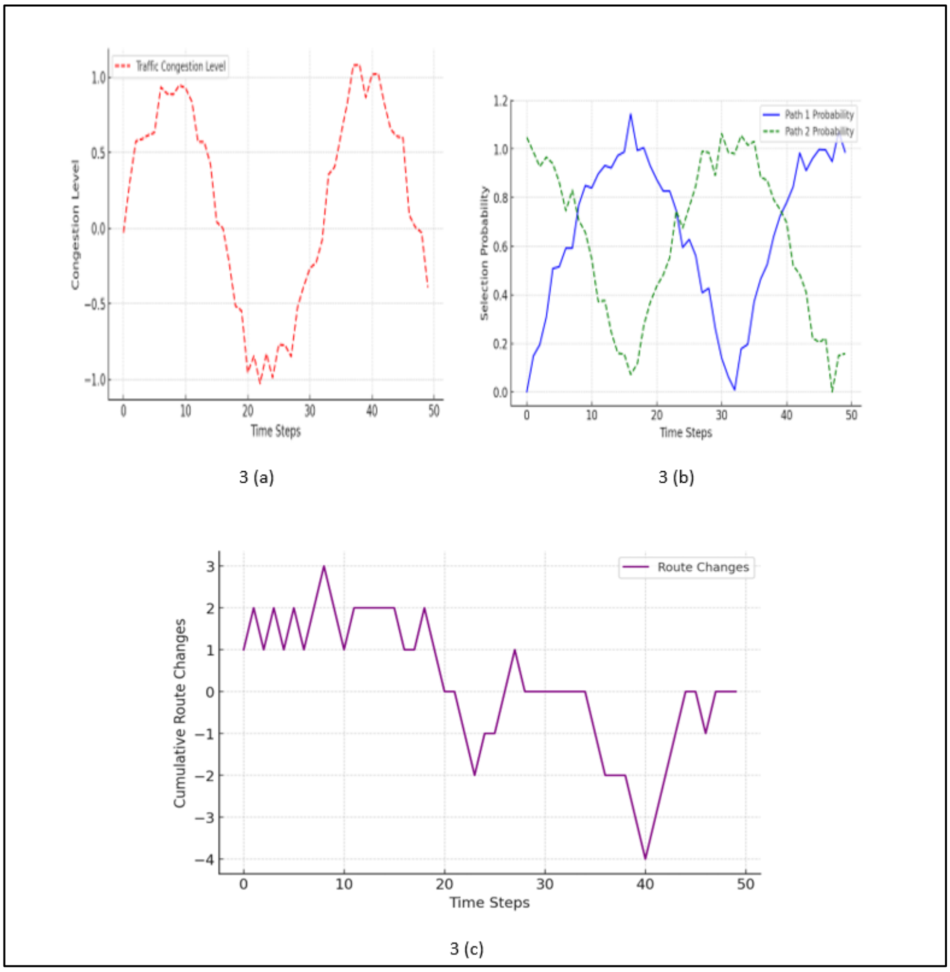

Figure 3 (a), 3 (b), 3 (c). Real-Time Traffic Behavior and Adaptive Path Selection in Smart City Routing

Figure 3(a) shows how traffic congestion levels fluctuate over time, emphasizing how real-time conditions and changes in vehicle flow cause congestion to shift dynamically. Path selection probabilities are depicted in Figure 3(b), where vehicles make adaptive decisions by dynamically selecting between two alternate routes based on optimization algorithms and congestion. Cumulative route changes are illustrated in Figure 3(c), which demonstrates how vehicles continuously modify their routes in response to traffic, rerouting choices, and real-time network updates. Together, these graphs show how MFO-PSO-ACO hybrid optimization is adaptive in controlling dynamic urban traffic for effective healthcare logistics in smart cities.

5. Conclusion

This study reveals the possibility of hybrid swarm optimization techniques that can be applied in combining Moth Flame Optimization (MFO), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) to improve smart city healthcare systems. By combining the strengths of these methods, the proposed hybrid approach significantly improves the efficiency of traffic routing in healthcare applications, ensuring timely and efficient transportation for critical services. The hybrid MFO-PSO-ACO optimization framework was successfully tested in a dynamic smart city traffic environment. The evaluation, based on time efficiency, throughput, scalability, and energy consumption, demonstrated its capability to enhance emergency response times and reduce congestion. The results confirm that shortest path optimization benefits from a well-integrated swarm intelligence approach, making the proposed method a scalable and adaptive solution for real-world smart city healthcare logistics. The findings were validated on the grounds of the ability of multiple optimization techniques to handle complex difficulties of dynamic environments, like traffic management, in real-time. This hybrid approach is scalable and robust, proving to be a potential tool for the infrastructures related to smart cities. Future research directions would extend this work with a focus on integrating machine learning models for predictive routing and adapting the hybrid approach toward other domains, including disaster management and emergency response systems.

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