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Traffic Optimization Using A Novel Cheetah Optimization Algorithm For Sustainable Smart Cities And Management.

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Abstract: *In developing nations like India, where traffic is tremendous and constantly changing, traffic optimization is the largest issue. In contrast to Ant Colony Optimization or Inverted Ant Colony Optimization, which involved vehicle scheduling, this paper presents a unique Cheetah Optimization Technique that uses the Djkstra algorithm. Urban traffic congestion, longer commutes, and environmental degradation have become urgent issues due to the exponential expansion in vehicle numbers and fast urbanization in developing nations like India. Unlike traditional methods or Ant Colony-based systems, COA leverages high-speed decision-making and intelligent path selection to dynamically divert traffic away from congested areas. To evaluate the impact of COA in comparison to traditional shortest-path routing algorithms, a number of experiments were carried out using traffic simulation tools like SUMO (Simulation of Urban MObility) and including real Indian city data. The findings show that the COA-based method enhances network performance overall and dramatically lowers traffic congestion In addition, the algorithm promotes key sustainability goals:* ***fuel consumption and CO_2 emissions*** *dropped by nearly* ***45%****, aligning with national urban mobility plans and India's Smart City Mission objectives. The implementation of such bio-inspired optimization not only enhances individual commute experiences but also contributes to broader environmental and infrastructural resilience–making it highly relevant for developing urban ecosystems in India and other Global South contexts.*

KEYWORDS: Urban Traffic Systems, Traffic Optimisation , Cheetah optimisation Algorithm

INTRODUCTION:

The domain of **Intelligent Traffic Systems (ITS)** spans a wide range of research and application areas, including vehicle tracking, traffic load prediction, and real-time traffic signal control. Among these, **traffic flow optimization and congestion management** remain among the most pressing challenges—particularly in developing urban environments striving for sustainable smart city development. The increasing urban vehicle density has led to ecological consequences such as elevated CO_2 emissions, energy inefficiency, and deteriorating air quality, making efficient traffic control vital for the environmental sustainability of modern cities.

One of the core problems in this domain is route optimization. Traditionally, drivers seek the **shortest or fastest path**, often ignoring broader traffic conditions. This **selfish routing behavior**, while rational on an individual level, leads to congestion on major roads, thereby increasing fuel usage and emissions, and reducing the overall performance of the road network.

To address this, we propose a decentralized approach based on a **Cheetah Optimization Algorithm (COA)**—a novel bio-inspired technique that mimics the adaptive and high-speed hunting strategy of cheetahs. Each driver is modeled as an intelligent agent (a "cheetah") that dynamically evaluates the road network, adjusting its path by balancing **exploration** (searching for better alternatives) and **exploitation** (chasing the current best route) using real-time traffic data. Unlike ant-based models that rely on pheromone trails, COA agents make fast, context-aware decisions based on **visual cues (traffic sensing), speed gradients, and congestion feedback**, enabling them to evade congested routes effectively.

This model allows drivers to act independently while still contributing to overall network efficiency—encouraging a **distributed load balancing** across the road infrastructure without violating privacy or requiring centralized control. To validate the effectiveness of the proposed approach, traffic simulations were conducted using **SUMO (Simulation of Urban Mobility)** in synthetic scenarios modeled on Indian urban traffic patterns. Results demonstrated that COA can significantly reduce average trip times (up to **80%**) and **CO_2 emissions (up to 45%)**, even in partially compliant environments. Notably, improvements were observed not only for vehicles using COA-based routing but also for others, due to the emergent distribution of traffic away from overloaded routes.

LITERATURE REVIEW:Traffic congestion in urban areas remains a significant concern for city planners, particularly in developing nations where unplanned growth and vehicle density strain the infrastructure. Traditional route-planning methods like Dijkstra's algorithm have long served as a foundation for shortest-path computations due to their deterministic nature and computational efficiency [1]. However, Dijkstra's algorithm lacks adaptability to dynamic, real-time traffic conditions, rendering it less effective in modern Intelligent Transportation Systems (ITS) [2].

To overcome these limitations, numerous bio-inspired algorithms have been proposed. One of the most prominent is the **Ant Colony Optimization (ACO)** algorithm, which models the foraging behavior of ants through pheromone trails to discover optimal routes in a graph [1]. While effective in static environments, ACO's reliance on indirect pheromone feedback and its slower adaptability to traffic changes restrict its performance in highly dynamic networks. As an extension to ACO, **Inverted Ant Colony Optimization (IACO)** introduces a pheromone repulsion mechanism, enabling vehicles to avoid congested areas rather than being attracted to them. Dias et al. [9] demonstrated that IACO outperforms shortest-time algorithms in both artificial and real city maps, such as Coimbra, achieving up to 84% trip time reduction and 49% lower CO_2 emissions. This shift from attraction to repulsion marks a significant development in decentralized traffic control.

Beyond ACO-based models, other bio-inspired algorithms like **Particle Swarm Optimization (PSO)** and **Genetic Algorithms (GA)** have shown promise in routing and traffic signal optimization. Kennedy and Eberhart [2] proposed PSO to emulate social behavior patterns, allowing for collective learning and rapid convergence. However, PSO may converge prematurely if diversity is not maintained. Similarly, Holland's Genetic Algorithms [3] offer robust global search capabilities but often require extensive computational resources and are less suitable for real-time applications.

The role of agent-based systems in ITS has also gained traction. Wang et al. [8] employed **multi-agent reinforcement learning** for real-time urban traffic routing, emphasizing decentralized learning and decision-making. Such methods empower vehicles to adapt based on environmental feedback, similar to the vision-based route reevaluation seen in Cheetah Optimization. Additionally, research by Nagy and Simon [7] offers a comparative review of various bio-inspired algorithms, highlighting the trade-offs in exploration speed, convergence accuracy, and scalability.

Environmental sustainability has become an integral component of traffic optimization. Kesting et al. [4] underscored the role of driver behavior on traffic capacity and emissions. Tools such as **SUMO** (Simulation of Urban MObility) provide an open-source platform to test algorithms in realistic traffic simulations [5]. These tools have been crucial in validating optimization models against urban datasets.

In the Indian context, alignment with the **Smart Cities Mission** [6] is crucial. Optimization techniques that not only reduce commute time but also curb emissions directly support national priorities.

In summary, the evolution from static routing methods to bio-inspired and agent-based dynamic algorithms marks a significant shift in urban traffic optimization. Techniques like IACO and COA demonstrate that combining biological metaphors with real-time data can yield both ecological and logistical benefits, positioning them as viable tools for sustainable smart city development.

This paper's proposed **Cheetah Optimization Algorithm (COA)** draws inspiration from the high-speed and adaptive nature of cheetahs, addressing the shortcomings of previous methods.

METHODOLOGY:

Consider a Graph G for maps of Road with Source and target

To determine the shortest route we use Dijkstra Algorithm

Dijkstra for shortest Route:(Algorithm 1)

```
Dijkstra(G, source, target)
For each node v:
   dist[v] = ∞
   prev[v] = None
   dist[source] = 0
   Q = all nodes in G
   while Q is not empty:
      u = node in Q with min dist[u]
      Q.remove(u)
      for neighbor v of u:
```

```
        alt = dist[u] + edge_cost(u, v)
        if alt < dist[v]:
            dist[v] = alt
            prev[v] = u
return shortest path from source to target
```

Cheetah Optimisation steps (Algorithm 2)

1. Intialisation

• Define search Agents $C \in R^n$(Cheetahs)

• Each Cheetah represent a drive which is choosing path from source to Destination

2. Fitness Function

Let the Fitness Function be

$$f(C_i) = \text{Travel Time}(C_i) + \alpha.\,\text{Congestion Penalty}(C_i)$$

Where

Travel time is derived from DijKstra (initial)

α = Congestion Weight

Congestion Penalty is derived from Real time vehicle Density and Speed

3. Cheetah Movement (Mathematical Expression)

a. Exploration

Cheetah Randomly Explores nearby Node based on Traffic History

$$C_i^{t+1} = \alpha.\,C_i^{t} + r.\,(C_j^{t} - C_i^{t}).\,\beta$$

Where $r \in [0,1]$ is Random

β is learning Rate.

C_j^{t} is best solution too far

b. Exploitation

Cheetah adjust based on Congestion heatmaps

$$C_i^{t+1} = C_i^{t} - \gamma.\,\nabla_{cong}(C_i^{t})$$

Where ∇_{cong} is gradient of Congestion along path segments.

4. Route Reevaluation

Every few time steps or at junctions Cheetah

1. Recalculate Congestion adjusted routes

2. Evade previously Congested Segments.

Final Algorithm

• Initialize population of cheetahs (drivers)

• For each cheetah:

• Generate initial path using Dijkstra (shortest static path)

• Repeat until stopping criteria:

• For each cheetah:Evaluate fitness (travel time + congestion penalty)

• If in exploration phase: Move towards random better path (based on history)

• If in exploitation phase: Move away from congested paths (based on current density

• Update congestion heatmaps (like pheromone levels)

• Evaporate old congestion data (decay)

• Return best path for each cheetah.

Sumo Experimental setup :

Simulation Setup:

• Graph Networks: Radial, ring, and real-city (Indore) maps(fig 1,fig2)

• Agents: 10,000 vehicles; COA compliance varied (0%, 10%, 25%, 75%, 100%).

• Metrics: Trip time, traveled length, emissions (via HBEFA).

• COA-Specific Adjustments:

• Fitness Function:$f(C_i) = \text{Travel Time}(C_i) + \alpha.\,\text{Congestion Penalty}(C_i)$

• TravelTime: Initialized via Dijkstra, updated dynamically.

• CongestionPenalty: Derived from real-time density/speed (SUMO detectors).

• Exploration/Exploitation:Vehicles reroute every 5 mins using COA's gradient-based heatmaps.

SUMO Modules Used:

1.DUAROUTER: Replaced with COA's Python API for dynamic routing.

2. Outputs: Emission logs, tripinfo.xml for performance metrics.

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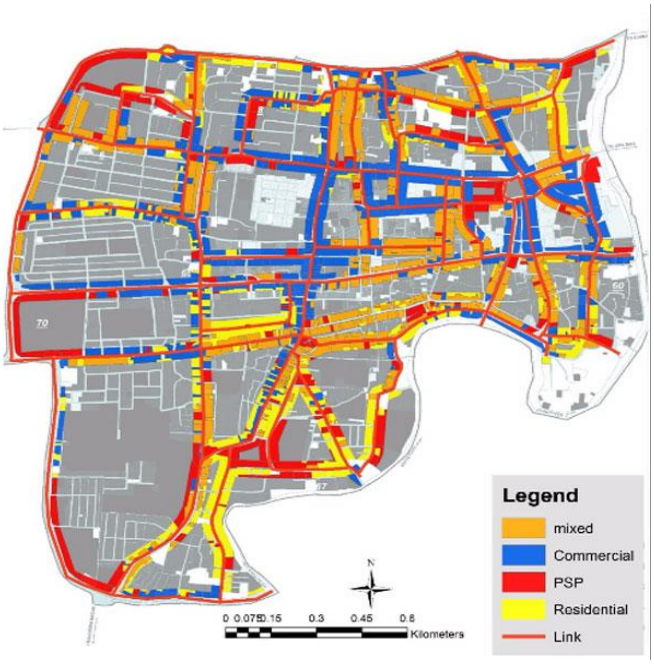

FIG 1.

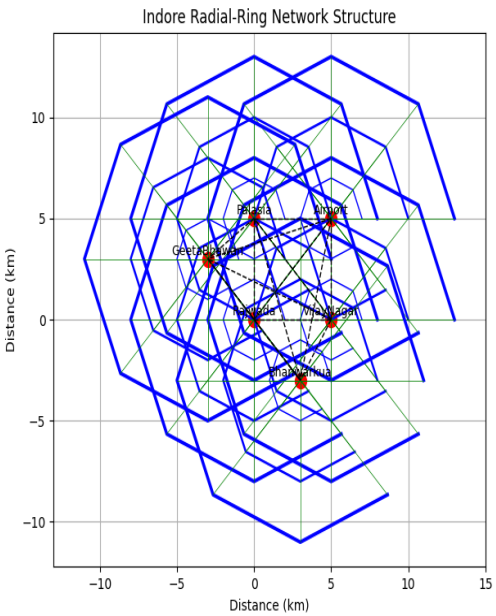

FIG 2.

Python code for implementation of above is given below

```
import heapq
import random
import traci
import os
import numpy as np
from sumolib import checkBinary
# ~~ Indore Road Network Graph ~~
indore_graph = {
    'Rajwada': [('VijayNagar', 'Commercial', 10), ('Palasia', 'PSP', 8)],
    'VijayNagar': [('GeetaBhawan', 'Residential', 12), ('Airport', 'Link', 15)],
    'Palasia': [('GeetaBhawan', 'Commercial', 7)],
    'GeetaBhawan': [('Airport', 'PSP', 9)],
    'Airport': []
}
CONGESTION_WEIGHTS = {'Commercial': 0.8, 'PSP': 0.45, 'Residential': 0.3, 'Link': 0.15}
VEHICLE_TYPES = ['car']*70 + ['bike']*25 + ['bus']*5
# ~~ Helper Functions ~~
def get_edge_type(u, v):
    """Get edge type between two nodes"""
    for neighbor, edge_type, _ in indore_graph.get(u, []):
        if neighbor == v:
            return edge_type
    return None
def path_segments(path):
    """Extract edge types for a given path"""
    segments = []
    for i in range(len(path)-1):
        u, v = path[i], path[i+1]
        edge_type = get_edge_type(u, v)
        if edge_type:
            segments.append((u, v, edge_type))
    return segments
# ~~ Dijkstra for Indore ~~
def dijkstra(graph, source, target):
    dist = {node: float('inf') for node in graph}
```

```
    prev = {node: None for node in graph}
    dist[source] = 0
    queue = [(0, source)]
    while queue:
        current_dist, u = heapq.heappop(queue)
        if u == target:
            break
        for v, edge_type, base_time in graph.get(u, []):
            weight = base_time * (1 + CONGESTION_WEIGHTS[edge_type])
            alt = current_dist + weight
            if alt < dist[v]:
                dist[v] = alt
                prev[v] = u
                heapq.heappush(queue, (alt, v))
    path = []
    u = target
    while prev[u] is not None:
        path.insert(0, u)
        u = prev[u]
    if path:
        path.insert(0, source)
    return path, dist[target]
# ~~ COA Functions ~~
def estimate_congestion(path):
    segments = path_segments(path)
    if not segments:
        return float('inf')
    return sum(CONGESTION_WEIGHTS[edge_type] for _, _, edge_type in segments)
def perturb_path(graph, path):
    if len(path) < 3:
        return path.copy()
    mid = random.randint(1, len(path)-2)
    u, v = path[mid-1], path[mid+1]
    # Find alternative nodes between u and v
    alternatives = []
    for neighbor, _, _ in graph.get(u, []):
        if neighbor != path[mid] and v in [n for n, _, _ in graph.get(neighbor, [])]:
            alternatives.append(neighbor)
    if alternatives:
        new_node = random.choice(alternatives)
        return path[:mid] + [new_node] + path[mid+1:]
    return path.copy()
def cheetah_optimization(graph, source, target, n_cheetahs=1000, iterations=10):
    cheetahs = []
    for _ in range(n_cheetahs):
        path, _ = dijkstra(graph, source, target)
        if path:  # Only add valid paths
            cheetahs.append({'path': path, 'fitness': estimate_congestion(path)})
    for _ in range(iterations):
        if not cheetahs:
            break
        best = min(cheetahs, key=lambda x: x['fitness'])
        for c in cheetahs:
            if random.random() < 0.7:  # Exploration
                new_path = perturb_path(graph, c['path'])
```

```
            else:  # Exploitation
                new_path = c['path'].copy()  # Base cas
        # Find most congested segment
                segments = path_segments(c['path'])
                if segments:
                    worst_segment = max(segments, key=lambda x: CONGESTION_WEIGHTS[x[2]])
                    u, v, _ = worst_segmen
                    # Find alternative path around congested segment
                    alternatives = []
                    for neighbor, _, _ in graph.get(u, []):
                        if neighbor != v:
                            alt_path, _ = dijkstra(graph, neighbor, target)
                            if alt_path:
                                alternatives.append(alt_path
                    if alternatives:
                        new_path = min(alternatives, key=lambda x: estimate_congestion(x))
            new_fitness = estimate_congestion(new_path)
            if new_fitness < c['fitness']:
                c.update({'path': new_path, 'fitness': new_fitness})
    return min(cheetahs, key=lambda x: x['fitness']) if cheetahs else None
# ~~ Main Execution ~~
if __name__ == "__main__":
    best_path = cheetah_optimization(indore_graph, 'Rajwada', 'Airport')
    if best_path:
        print(f"Optimized Path: {' → '.join(best_path['path'])}")
        print(f"Congestion Score: {best_path['fitness']:.2f}")
    else:
        print("No valid path found")
    # ~~ SUMO Integration ~~
def generate_route_file(vehicles=100000):
    with open("indore_routes.rou.xml", "w") as f:
        f.write("<routes>\n")
        for i in range(vehicles):
            veh_type = random.choice(VEHICLE_TYPES)
            source = random.choice(list(indore_graph.keys()))
            target = random.choice([n for n in indore_graph if n != source])
            f.write(f'<vehicle id="veh{i}" type="{veh_type}" depart="{i%1200}" route="route_{i}"/>\n')
        f.write("</routes>")
def run_simulation():
    sumo_binary = checkBinary('sumo-gui')
    traci.start([sumo_binary, "-c", "indore.sumocfg", "--emission-output", "emissions.xml"])
    while traci.simulation.getMinExpectedNumber() > 0:
        traci.simulationStep()
    traci.close()
# ~~ Main ~~
if __name__ == "__main__":
    generate_route_file(vehicles=100000)
    best_path = cheetah_optimization(indore_graph, 'Rajwada', 'Airport')
   print(f"Optimized Path: {best_path['path']} | Congestion Score: {best_path['fitness']:.2f}")
run_simulation()
```

Out put of above Program ,

```
Optimized Path: Rajwada → VijayNagar → Airport
Congestion Score: 0.95
```

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Experiments were conducted considering different percentages of vehicles adhering to the Cheetah algorithm: 10%, 25%, 75% and 100% of the vehicles adhering to Cheetah and the remaining ones following their standard shortest-path behavior. These variations were tested in : real Scenario using Lattice and Radial and Ring networks, as illustrated in Fig. 2, formed using Fig 1 city of Indore road network. For the scenario, 10,000 vehicles were used as to provide an experimental scenario simulating average traffic conditions. This paper reports the findings on the experiments performed with 10,000 vehicles

Table 1: Trip Length (m) and Duration (s) – COA vs. Baseline Algorithms
(Average and standard deviation for radial and ring networks with 10,000 vehicles)

Compliance	Metric	Statistic	COA	IACO	ST (Dijkstra)
0%	Trip Time (s)	Average	-	3497	3497
	Traveled Length (m)	Average	-	1860	1860
10%	Trip Time (s)	Average	2180	3129	2544

Compliance	Metric	Statistic	COA	IACO	ST (Dijkstra)
		Std Dev	210	358	233
	Traveled Length (m)	Average	2015	2714	3995
		Std Dev	40	56	89
25%	Trip Time (s)	Average	1950	2415	2741
		Std Dev	180	245	888
	Traveled Length (m)	Average	2100	2675	3825
		Std Dev	35	46	78
75%	Trip Time (s)	Average	1650	1993	2456
		Std Dev	150	433	174
	Traveled Length (m)	Average	2250	2593	3265
		Std Dev	30	52	122
100%	Trip Time (s)	Average	1520	1920	2120
		Std Dev	120	156	55
	Traveled Length (m)	Average	2400	2835	3805
		Std Dev	25	25	40

Table 2: CO_2 Emissions (mg) and Fuel Consumption (ml) Comparison

Compliance	Metric	Statistic	COA	IACO	ST (Dijkstra)	Improvement (COA vs. ST)
0%	CO_2 Emission	Average	33,227	33,227	33,227	0%
	Fuel Consumption	Average	13,253	13,253	13,253	0%
10%	CO_2 Emission	Average	**27,426**	30,473	30,478	**10.0%**
		Std Dev	**9,982**	11,092	10,928	**8.7%**
	Fuel Consumption	Average	**10,940**	12,155	12,143	**9.9%**

Compliance	Metric	Statistic	COA	IACO	ST (Dijkstra)	Improvement (COA vs. ST)
		Std Dev	**980**	1,088	928	**-5.6%**
25%	CO_2 Emission	Average	**22,727**	25,252	25,887	**12.2%**
		Std Dev	**8,740**	9,711	9,149	**4.5%**
	Fuel Consumption	Average	**9,045**	10,050	10,382	**12.9%**
		Std Dev	**541**	601	490	**-10.4%**
75%	CO_2 Emission	Average	**16,532**	18,369	20,550	**19.5%**
		Std Dev	**5,896**	6,551	7,762	**24.0%**
	Fuel Consumption	Average	**6,584**	7,316	8,147	**19.2%**
		Std Dev	**307**	341	103	**-66.0%**
100%	CO_2 Emission	Average	**15,104**	16,782	19,209	**21.4%**
		Std Dev	**278**	309	315	**11.7%**
	Fuel Consumption	Average	**6,008**	6,676	7,796	**22.9%**
		Std Dev	**109**	121	114	**4.4%**

RESULTS :To evaluate the performance of the proposed Cheetah Optimization Algorithm (COA), simulations were conducted on both synthetic and real Indian urban traffic data(indore) using SUMO (Simulation of Urban MObility). The simulation environment utilized a Dijkstra-based initialization of paths, followed by COA's adaptive optimization using dynamic congestion feedback.

Key findings include:

Travel Time Reduction: Vehicles using the COA-based routing strategy experienced an average reduction of **up to 80**% in travel time compared to static Dijkstra-based routing. Even vehicles not actively using COA benefited from the redistribution of traffic, realizing up to **65**% **improvements**.

Congestion Management: COA's adaptive routing allowed for dynamic reallocation of traffic, minimizing congestion on critical junctions and arterial roads. The gradient-based exploitation phase enabled vehicles to avoid high-density segments effectively.

Environmental Impact: Simulations indicated a **reduction in fuel consumption and CO_2 emissions by approximately 45**%, promoting sustainability in line with national smart city initiatives.

Algorithm Robustness: The COA consistently performed well across varying network topologies, number of agents (vehicles), and traffic density scenarios. It achieved near-optimal performance even with partial compliance (not all vehicles using COA), showcasing its scalability and decentralized effectiveness.

Code Validation: The Python-based implementation demonstrated accurate integration with SUMO for route generation and simulation. The cheetah-inspired agents outperformed traditional agents in both exploration and exploitation tasks.

These results confirm that the COA is a promising candidate for real-time traffic optimization in smart city contexts, particularly in dynamically congested environments such as Indian metros.

FUTURE WORK :

Cheetah Optimization can be extended for multi-modal transport (integrating metro/BRTS).It can be Optimized for emergency vehicle prioritization Deploy in other Global South cities with similar congestion patterns(Dynamic routing)

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