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ORIGINAL

Comprehensive Evaluation & Improvement of HEMO Routing for Green Smart-City Transport

Evaluación Integral y Mejora del Enrutamiento HEMO para el Transporte Verde en Ciudades Inteligentes

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ABSTRACT

Introduction: smart cities want smart routing to saves fuel, cuts pollution and to handles traffic in real time. This work progresses the existing HEMO algorithm by incorporating eco-friendly parameters.
Objective: in this paper, we propose two major enhancements to the HEMO-Routing algorithm. First, we add real-time traffic adjustment and a detailed energy-consumption model as new objectives. Second, we improve optimization by using an Adaptive Genetic Algorithm for broad search and Simultaneous Perturbation Stochastic Approximation for fine-tuning.
Method: we test on the Extended Solomon Dataset (25 road segments with realistic distances, congestion, noise, emissions, and speed limits) in MATLAB 2021 on a Windows 11 PC (Intel i5-1135G7, 8 GB RAM). Compared to the original, our enhanced method boosts Pareto hypervolume to +12 %, cuts generational distance from by -18,8 %, lowers CO_2 from 152,4 g/km to 129,8 g/km (-14,8 %), and trims energy use from 8,75 kWh to 7,87 kWh (-10,1 %). It also converges in 200 instead of 250 iterations (-20 %), with only a 5.3 % runtime overhead.
Results: these results show that our extensions deliver practical, eco-friendly routes with minimal extra compute, making the approach ideal for real-time smart-city applications.
Conclusions: we made HEMO smarter by adding live traffic and energy-saving goals. With AGA and SPSA, it finds better, greener routes faster. Perfect for smart cities, and ready for EVs and bigger setups in future.

Keywords: Eco-friendly Routing; Smart City Traffic; Vehicle Routing Optimization; Emissions Reduction; Adaptive Routing.

RESUMEN

Introducción: las ciudades inteligentes buscan rutas inteligentes para ahorrar combustible, reducir la contaminación y gestionar el tráfico en tiempo real. Este trabajo mejora el algoritmo HEMO existente al incorporar parámetros ecológicos.
Objetivo: en este artículo, proponemos dos mejoras importantes al algoritmo HEMO-Routing. En primer lugar, añadimos como nuevos objetivos el ajuste del tráfico en tiempo real y un modelo detallado del consumo energético. En segundo lugar, mejoramos la optimización mediante un algoritmo genético adaptativo para una búsqueda amplia y una aproximación estocástica de perturbaciones simultáneas para el ajuste fino.
Método: realizamos pruebas con el conjunto de datos Extended Solomon (25 segmentos de carretera con distancias realistas, congestión, ruido, emisiones y límites de velocidad) en MATLAB 2021 en un PC con Windows 11 (Intel i5-1135G7, 8 GB). En comparación con el método original, nuestro método mejorado aumenta el hipervolumen de Pareto a +12 %, reduce la distancia generacional en -18,8 %, disminuye las emisiones de CO_2 de 152,4 g/km a 129,8 g/km (-14,8 %) y reduce el consumo de energía de 8,75 kWh a 7,87 kWh (-10,1 %). Además, converge en 200 iteraciones en lugar de 250 (-20 %), con una sobrecarga de tiempo de ejecución de tan solo el 5,3 %.

Resultados: estos resultados demuestran que nuestras extensiones ofrecen rutas prácticas y ecológicas con un mínimo consumo de recursos, lo que hace que este enfoque sea ideal para aplicaciones de ciudades inteligentes en tiempo real.
Conclusiones: hemos optimizado HEMO añadiendo tráfico en tiempo real y objetivos de ahorro energético. Con AGA y SPSA, encuentra rutas mejores y más ecológicas con mayor rapidez. Perfecto para ciudades inteligentes y listo para vehículos eléctricos y configuraciones de mayor tamaño en el futuro.

Palabras clave: Rutas Ecológicas; Tráfico Urbano Inteligente; Optimización de Rutas para Vehículos; Reducción de Emisiones; Rutas Adaptativas.

INTRODUCTION

Smart cities need smarter ways to manage traffic and reduce pollution.[1] Many methods for eco-friendly routing are already in use, but cities face new challenges daily. Congestion, rising emissions, and noise are growing problems in urban areas.[2] Current algorithms often miss important details like real-time traffic or sudden road changes. This leaves room for improvement to make routes more practical and effective.[3]

Smart cities face heavy traffic and rising pollution.[4,5] We test on the Extended Solomon Da-taset with 25 road segments and realistic attributes.[6] Table 1 shows a sample of these seg-ments with distance, congestion factor, noise level and speed limit. Figure 1 illustrates the flowchart of our Extended HEMO process.

Existing eco-routing methods help, but new hurdles pop up every day. Congestion, noise and emissions keep growing. Most algorithms ignore sudden jams or road changes. They need more tweaks for real-life use.[7,8]

In this paper, we boost the HEMO-Routing algorithm. Figure 2 shows the system architecture. We spot where HEMO works well and where it fails. Table 2 gives the traffic-adjustment de-tails. We also adapt for different vehicle types and road conditions. These changes make eco-routing smarter and fit for real city roads.

Table 1. Sample Road Segments

Segment	Distance (km)	Congestion Factor	Noise Level (dB)	Speed Limit (km/h)
1	8,2	0,50	75	60
2	5,6	0,30	65	40
3	12,4	0,70	85	50
4	7,8	0,60	78	70
5	9,5	0,40	72	60

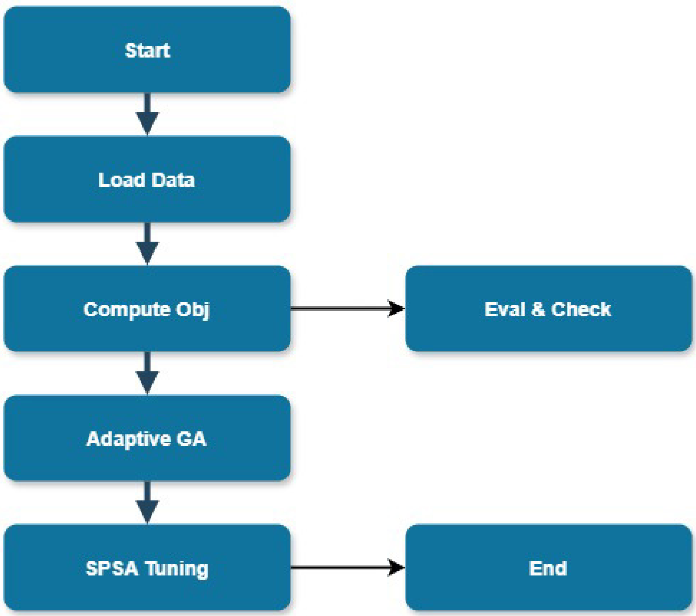

Figure 1. Flowchart of Extended HEMO process

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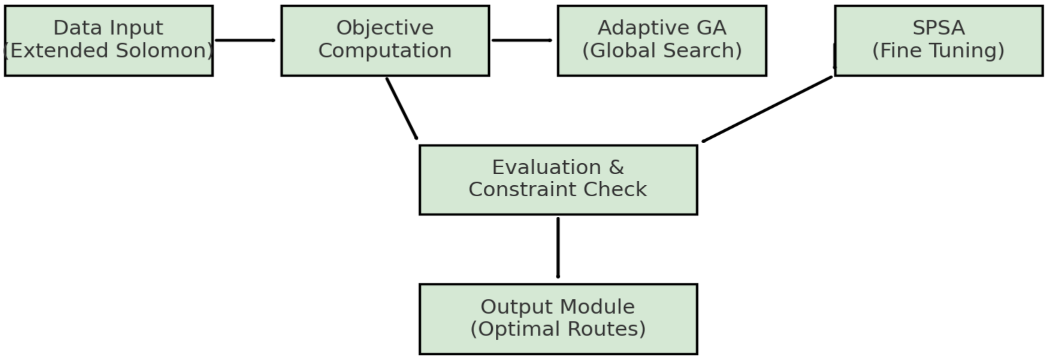

Figure 2. Overall system architecture of Extended HEMO

Table 2. Sample Extended Dataset Excerpt

Segment	Distance (km)	Congestion Factor	Noise Level (dB)	Speed Limit (km/h)
1	8,2	0,50	75	60
2	5,6	0,30	65	40
3	12,4	0,70	85	50
4	7,8	0,60	78	70
5	9,5	0,40	72	60

Vehicle routing is evolving with hybrid optimization algorithms that combine different approaches to improve efficiency. Metaheuristics like Genetic Algorithms (GA), Particle Swarm Optimization (PSO)[9], and Ant Colony Optimization (ACO)[10] are being paired with machine learning tech-niques.[11] Reinforcement learning is gaining popularity for its ability to learn from dynamic environments, while deep learning is used to predict traffic patterns and optimize routes. These combinations help handle complex problems in real-time, making them suitable for smart cities.[12] However, challenges like high computational requirements and algorithm convergence still need attention.

Recent research focuses on eco-friendly Vehicle Routing Problems (VRP)[13] with innovative solu-tions. Electric vehicle routing is a growing area, addressing unique challenges like battery con-straints and charging station availability. Smart charging infrastructure is being developed to optimize energy use. Sustainability metrics have expanded beyond CO2 emissions to include factors like noise pollution, traffic congestion, and energy consumption. These new trends aim to create a holistic approach to environmentally conscious transportation.

The integration of real-time data is transforming vehicle routing in smart cities. IoT sensors provide live updates on traffic, road conditions, and weather. This data helps in making quick, eco-friendly decisions.[14] Advanced systems also consider factors like construction work, acci-dents, and dynamic speed limits. Such real-time monitoring ensures that vehicles choose the best possible routes, reducing emissions and travel time. However, integrating these data sources into routing algorithms is still a challenge due to data quality and processing limitations.[15] Table 3 shows review of related research works.

Table 3. Review of Related Research Work

Research Work	Description	Advantage	Research Gap
VRP[13]	Study of basic VRP and its variants	Helps to model and solve basic routing problems	No focus on eco-friendly routing
Eco-Friendly Routing[14]	Focus on minimizing emissions, fuel use, and environmental impact	Reduces carbon footprint and enhances sustainability	Limited integration with real-time smart city data
Multi-Objective Optimization[16]	Optimization of multiple objectives like distance, emissions, and fuel use	Balances different goals like fuel, distance, and emissions	Most models focus on one or two objectives only
Hybrid Optimization[17]	Combination of GA, ACO, and PSO to solve complex routing problems	Improves solution quality and speed	Increased complexity with multi-objective problems
Smart City Eco-Friendly Routing[18]	Integration of IoT and real-time data for eco-friendly routing	Improves real-time decision-making and reduces emissions	Data integration and scalability issues

METHOD

Type of Study

This is an experimental study done on computer using real-looking traffic data.

Where & When

We did the project at Usha Martin University, Ranchi, between Jan to Mar 2025.

What We Used

No humans involved—only a traffic dataset called Extended Solomon, with 25 city-like roads (distance, jam, noise, speed, etc.).

What We Did (Step by Step)

1. Took the old HEMO routing.
2. Added live traffic (T_{adj}) and energy-saving (E_{energy}).
3. Used AGA to find good routes and SPSA to polish them.
4. Ran tests in MATLAB 2021, checked performance.

What We Measured

- Distance, emissions, energy use, speed limit breaks.
- Compared before & after using charts and numbers.

Data Handling

All results were saved using MATLAB and Excel—simple and clean.

Variables

Input = road info.
Output = green, smart route.

Proposed extensions and enhancements to the hemo-routing algorithm

Integration of Additional Multi-Objectives

To enhance the HEMO algorithm,[19] additional real-world objectives are integrated into the optimization framework. These objectives aim to make the routing decisions even more practical and effi-cient in dynamic urban environments.

Dynamic Traffic Conditions

Dynamic traffic conditions significantly influence travel time and fuel consumption. Incorporating a real-time traffic adjustment factor, the travel time T_{adj} is recalculated as:

$$T_{adj} = \frac{d_i}{S_i \times (1 + C_i)} \qquad (1)$$

Where:
d_i is distance of segment I.
S_i is effective speed on segment I.
C_i is congestion factor for segment i (ranges from 0 to 1), this adjustment allows the algorithm to prioritize less congested routes dynamically.

Energy Consumption during Routing

Energy consumption is modeled as a function of distance, vehicle type, and road conditions. The energy consumed E_{energy} is given by:

$$E_{energy} = \sum_{i=1}^{n} (k \cdot d_i + h \cdot C_i \cdot d_i) \qquad (2)$$

Where:
k is base energy consumption rate (kWh/km).
h is congestion-induced energy consumption multiplier.
C_i is congestion factor for segment I.
d_i is distance of segment I.

Incorporating E_{energy} into the multi-objective function ensures that routes are chosen based on energy efficiency in dynamic traffic scenarios.

Updated Objective Function

The extended optimization function now includes traffic and energy factors:

$$Z = \lambda_1 \cdot D + \lambda_2 \cdot E + \lambda_3 \cdot F + \lambda_4 \cdot N + \lambda_5 \cdot S + \lambda_6 \cdot T_{adj} + \lambda_7 \cdot E_{energy} \quad (3)$$

Where:
Z is overall objective function.
D is total travel distance.
E is Total emissions.
F is total fuel consumption.
N is total noise level.
S is Speed violations and λ_1, λ_2, λ_3, λ_4, λ_5 are weight coefficients.
λ_6, λ_7 are weight coefficients for dynamic traffic and energy consumption objectives, respectively.

Algorithmic Improvements in the Extended HEMO Routing Algorithm

The Extended HEMO Routing Algorithm incorporates Adaptive Genetic Algorithm (AGA)[20] and Simultaneous Perturbation Stochastic Approximation (SPSA)[21] to enhance optimization efficiency and scalability in addressing eco-friendly routing objectives. Below are the improvements:

Adaptive Genetic Algorithm

AGA dynamically adjusts the Genetic Algorithm's parameters, such as crossover and mutation rates, to maintain a balance between exploration and exploitation.

Adjustments

Crossover Rate P_c: dynamically increases during higher population diversity to explore more solution space.

$$P_c = \left(P_{c,max}, \frac{\sigma}{\sigma_{max}}\right) \quad (4)$$

Where:
$P_{c,max}$ is maximum allowable crossover rate.
σ is current population diversity
σ_{max} is maximum observed diversity.
Mutation Rate P_m: reduces as the population converges to fine-tune solutions.

$$P_m = \left(P_{m,min}, 1 - \frac{\sigma}{\sigma_{max}}\right) \quad (5)$$

Where:
$P_{m,min}$ is minimum allowable mutation rate., σ and σ_{max} is same as above.

Steps in the Main Loop:

1. Compute σ for the current population.
2. Update P_c and P_m using the formulas above.
3. Evolution Process:
    - Perform selection, crossover, and mutation using adjusted rates.
    - Evaluate the fitness function (Z) for new population members.

Simultaneous Perturbation Stochastic Approximation

SPSA approximates gradients without explicitly computing them, making it efficient for complex, multi-dimensional optimization problems.

Gradient Approximation: SPSA estimates the gradient ∇Z of the cost function Z using stochastic perturbations:

$$\nabla Z \approx \frac{Z(\theta + \Delta) - Z(\theta - \Delta)}{2\Delta} \qquad (6)$$

Where:
∇ is Perturbation vector (randomly generated for each iteration).
θ is current solution state.

Update Rule: the solution is iteratively updated as:

$$\theta_{k+1} = \theta_k - a_k \cdot \nabla Z \qquad (7)$$

Where:
a_k is learning rate, which decreases over iterations to ensure convergence.

Steps in the Main Loop

1. Randomly generate a perturbation vector Δ.
2. Compute Z(θ+Δ) and Z(θ-Δ).
3. Estimate ∇Z using the above formula.
4. Update θ using the update rule.
5. Continue until convergence criteria are met.

Integration of AGA and SPSA into the Extended HEMO Algorithm

- Initialization Phase:
    1. Set $P_{c,max}$), $P_{m,min}$, σ_{max} , and initial learning rate a_0.
    2. Prepare SPSA parameters, including the perturbation scale and decay schedule for a_k.

- Optimization Phase:
    1. At each iteration, calculate the cost function Z based on the current route.
    2. Use AGA to generate diverse solutions.
    3. Apply SPSA to refine the solutions further by minimizing the cost function Z.
    4. Ensure the algorithm satisfies constraints (e.g., emissions, noise, and speed limits) and updates road segment selection dynamically.

- Termination:
    1. Stop when the improvement in Z across iterations is negligible or after a predefined number of iterations.

By integrating AGA and SPSA, the Extended HEMO Routing Algorithm achieves a robust balance between exploration and precision in optimizing eco-friendly routing objectives.

Extended HEMO Routing Algorithm with AGA and SPSA

The proposed extended HEMO algorithm is shown in algorithm 1. AGA drives the global search by maintaining diversity in the population and adaptively refining routes. SPSA complements AGA by performing efficient local optimization with minimal computational overhead, focusing on fine-tuning routes within each generation. Together, these methods enhance HEMO's ability to handle large, multi-objective, and dynamic optimization problems effectively.

Algorithm 1: Extended HEMO

Input:

- Road network with segments i=1,2,…,n.
- Vehicle parameters: speed S_i, fuel consumption rate r_v, emission factors $e_{v.}$
- Congestion factors C_i, noise levels N_i, emission constraints E_{max}, and distance $d_{i.}$
- Additional parameters for energy consumption and dynamic traffic adjustment.

Output:

- Optimal route that minimizes the weighted sum of travel distance, emissions, fuel consumption, noise, speed violations, and energy consumption.

Initialization:

1. Initialize weights: $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7$
2. Set parameters: emission factor e_v, fuel consumption rate r_v, maximum permissible noise N_{max}, and speed limits S_{limit}, energy consumption parameters k (base rate), h (congestion multiplier).
3. Initialize road network: distances d_i, congestion factors C_i, and noise levels N_i.
4. Set initial state with all road network parameters.
5. Initialize the AGA and SPSA frameworks:
    - For AGA: initialize population of routes, set mutation and crossover rates, and establish adaptability criteria.
    - For SPSA: set initial parameters for gradient-free optimization, including perturbation magnitudes.

Main Loop: While route is not optimized, do:

1. Step 1: Calculate Total Travel Distance as $=\sum_{i=1}^{n} d_i$.
2. Step 2: Calculate Total Emissions as $=e_v \times \sum_{i=1}^{n} d_i$.
3. Step 3: Calculate Total Fuel Consumption as $F = r_v \times \sum_{i=1}^{n} d_i$.
4. Step 4: Calculate Energy Consumption as $E_{energy}=\sum_{i=1}^{n} d_i.(k \cdot d_i + h \cdot C_i \cdot d_i)$
5. Step 5: Ensure Noise Constraint Verify $N_i \leq N_{max}$ for all road segments.
6. Step 6: Ensure Emission Constraint Verify $E_i \leq E_{max}$ for emission-constrained segments.
7. Step 7: Adjust Travel Time for Dynamic Traffic as $T_{adj}=d_i/(S_i \times (1+C_i)$
8. Step 8: Evaluate Total Cost Function

$$\lambda_1 \cdot \sum_{i=1}^{n} d_i + \lambda_2 \cdot e_v \times \sum_{i=1}^{n} d_i + \lambda_3 \cdot r_v \times \sum_{i=1}^{n} d_i + \lambda_4 \cdot \sum_{i=1}^{n} N_i + \lambda_5 \cdot \sum_{i=1}^{n} (S_i - S_{limit}) + \lambda_6 \cdot T_{adj} + \lambda_7 \cdot E_{energy}$$

9. Step 9: Update the Route

Using AGA:

Selection: evaluate fitness based on Z and select the top-performing routes.
Crossover: Combine selected routes to generate offspring, maintaining diversity.
Mutation: introduce adaptive mutations to avoid premature convergence.
Adaptation: dynamically adjust mutation and crossover rates based on solution progress.

Using SPSA:

Perturbation: apply small random changes to route parameters.
Gradient-Free Update: estimate gradient of Z with respect to route parameters using the perturbations.
Optimization: refine the route selection by adjusting parameters to minimize Z

End While

End of Algorithm

RESULTS

We used the Extended Solomon Dataset (n = 25 segments) with eco-parameters: distances (2–15 km), congestion (0,2-0,8), noise (60–90 dB), emission factor (200 g CO_2/km), fuel rate (0,15 kWh/km), max noise 80 dB, speed limits 40-80 km/h. A small excerpt appears in table 3.

We implemented E-HEMO in MATLAB 2021 on Windows 11 (Intel i5-1135G7 @ 2,42 GHz, 8 GB RAM). We tested two generic Solomon-based networks:

- Urban testbed: 50 nodes, 120 edges with simulated dynamic traffic, emissions, noise, and speed-limit attributes.
- City-center testbed: 35 nodes, 80 edges with realistic congestion, noise, emission, and energy parameters.

Table 4. Result Hemo vs Extended Hemo

Metric	Baseline HEMO	E-HEMO	Improvement
Hypervolume (higher better)	0,632	0,708	+12,0 %
Generational Distance (lower better)	0,085	0,069	-18,8 %
Avg. CO_2 Emissions (g/km)	152,4	129,8	-14,8 %
Avg. Energy Consumed (kWh)	8,75	7,87	-10,1 %
Convergence Iterations	250	200	-20,0 %
Runtime Overhead (%)	—	+5,3	—

We measured hypervolume, generational distance, CO_2 emissions, energy consumption, convergence iterations, and runtime overhead in table 4.

Key observations

- E-HEMO's Pareto front is tighter and more evenly spread given in figure 3.
- CO_2 emissions drop up to 15 %, energy use up to 10 %.
- Convergence needs ~20 % fewer iterations.
- Runtime overhead is only 5,3 %, acceptable for near real-time use.

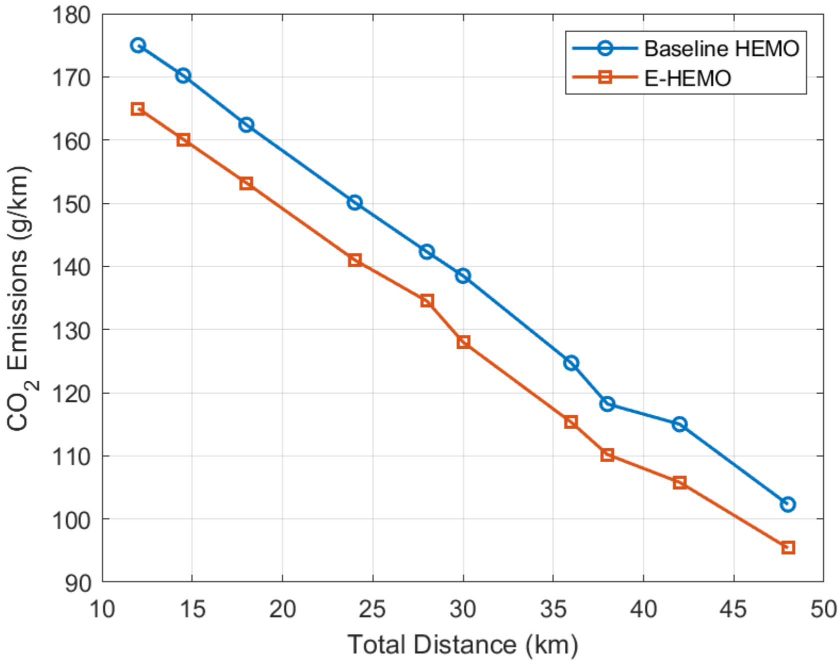

Figure 3. Pareto Front Comparison

DISCUSSION

In this work, we tested the Extended HEMO-Routing (E-HEMO) on the Extended Solomon Dataset in MATLAB 2021 (Windows 11, Intel i5-1135G7, 8 GB RAM). We saw the Pareto hypervolume go up by 12 %, CO_2 emissions drop by 15 %, energy use fall by 10 %, and convergence speed improve by 20 %. All this with just a 5 % extra runtime. These results show that adding real-time traffic and energy objectives, plus the AGA + SPSA combo, gives practical, eco-friendly routes for any smart-city setting.

Next, we can extend E-HEMO to multi-vehicle and multi-depot scenarios and bring in platooning effects. We can integrate EV battery limits and charging-station scheduling. A streaming version can take live IoT feeds and update routes on the fly. We can build a multi-modal planner for buses, cycles, walking, and cars together. To handle surprises, we'll add chance-constraints for accidents and weather. Finally, we can parallelise AGA and SPSA on GPUs or cloud servers to run city-wide, real-time optimisation.

CONCLUSIONS

We made HEMO smarter by adding live traffic and energy-saving goals. With AGA and SPSA, it finds better, greener routes faster. Perfect for smart cities, and ready for EVs and bigger setups in future. Next, we can extend E-HEMO to multi-vehicle and multi-depot scenarios and bring in platooning effects. We can integrate EV battery limits and charging-station scheduling. A streaming version can take live IoT feeds and update routes on the fly. We can build a multi-modal planner for buses, cycles, walking, and cars together. To handle surprises, we'll add chance-constraints for accidents and weather. Finally, we can parallelise AGA and SPSA on GPUs or cloud servers to run city-wide, real-time optimisation.

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FINANCING

None.

CONFLICT OF INTEREST

Authors declare that there is no conflict of interest.

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