International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 8, 2025
https://theaspd.com/index.php

# Heuristic Algorithm-Based Energy Optimization In Transportation To Reduce Carbon Emission

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***Abstract***
*India's transportation industry is entering a stage of high-quality development which has increased the quantity of carbon emissions and greenhouse gas (GHG) production. This is effecting the lives of millions of people in the rural as well as urban areas. In order to protect the environment and the health of people, government is focusing on the implementation of green and low-carbon transportation system which could reduce carbon emission to a significant extent. This paper thoroughly analyzes the main sources contributing to carbon emission in the transportation industry such as coal, gasoline, and diesel and predict their carbon emissions. It also focuses on the count of vehicles in 2023 which release significant amount of carbon in the environment. Particle Swarm Optimization (PSO) as a heuristic optimization technique was used to determine the optimal shift in vehicle population to EVs, aiming to minimize overall carbon emissions. The algorithm was used to find the optimal shift percentages for different vehicle types (two-wheelers, cars, goods vehicles, buses) towards electric vehicles to minimize carbon emissions. Results indicated that the PSO model has the highest degree of fit between the predicted value and the true value, which further illustrates the carbon emissions in the transportation industry. The PSO-optimized scenario yields a dramatic $CO_2$ cut of ~71%, with the total road transport $CO_2$ falls from a baseline of 100.0 Mt to about 28.9 Mt. Each two-wheelers and cars drive large percentage drops, and even heavy trucks and buses showed substantial reductions in absolute terms. Accelerating the upgradation of the transportation structure by introducing green and low-carbon emission transportation system will be important measures to control carbon emissions and promote the sustainable development of the conveyance system.*
***Keywords:*** *Particle Swarm Optimization; $CO_2$ reduction; electric vehicles; greenhouse gas; sustainable development*

## I. INTRODUCTION

The rapid urbanization and industrialization has accelerated the energy consumption globally [1]. This releases a large amount of polluting gases, causing damage to the environment and seriously affecting people's lives [2]. Transportation industry is one of the major contributor towards global carbon emission. It accounts for approximately 15% of total greenhouse gas (GHG) emissions and nearly 25% of energy-related $CO_2$ emissions globally, which effects all the developed and developing nations equally [3,4] The primary carbon emission comes from the burning of fossil fuels like gasoline and diesel for transportation activities across road, air, rail, and sea networks, with road transport being the largest contributor [5]. A rising population, rapidly growing economy, and increased energy demand have seen India's emissions soar in recent decades, making it the third-largest contributor to global GHG emissions. India now emits around four billion metric tons of carbon dioxide equivalent ($CO_2e$) every year and is now projected to overtake the United States as the second-biggest emitter by 2035. Dominance of road transport in India, particularly freight trucks and passenger cars account for a significant portion of the total emission which largely depends on fossil fuels like petrol and diesel. India's GHG emissions grew by 6.1 percent in 2023 to reach a new high of 4.2 $GtCO_2e$, with the average person's carbon footprint reaching to 2.9 $tCO_2e$ in 2023.

**Table 1: Global Share of Transportation-Related $CO_2$ Emissions**

| Source | Emission Factor (%) | Main contributors |
|---|---|---|
| Road transport | 74 | Cars, trucks, buses, two-wheelers |
| Aviation | 12 | Commercial and private jets |
| Shipping | 10 | Cargo ships, tankers, fishing boats |
| Rail | 2 | Trains |
| Public transport | 2 | Buses (diesel, CNG, electric) |

Studies shows that major sources of energy consumption and carbon emissions comes from gasoline which constitutes around 40% of total transportation-related $CO_2$ emissions. Passenger cars, motorcycles, and light-duty trucks are the major contributors of gasoline. A standard gasoline-powered car emits approximately 2.3 kg of $CO_2$ per litre of fuel burned. Second major contributors of $CO_2$ emissions (~35%) are diesel vehicles like trucks, buses, ships, and locomotives [6]. A heavy-duty truck running on diesel emits about 2.7 kg of $CO_2$ per litre of fuel burned. Transportation associated with coal-based electricity generation like electric rail networks, electric buses, and EV charging emits ~5-10% of $CO_2$. Further, 10-12% of transportation-related emissions come from aviation, where a single long-haul flight emits around 1 ton of $CO_2$ per passenger. Major contributors are commercial airlines and private jets. Transportation through ships like cargos, tankers, and fishing vessels which uses Marine Fuel (Heavy Fuel Oil - HFO) emits around 10-15% of $CO_2$. A large container ship can emit as much $CO_2$ annually which is equivalent to the emission from 50 million cars. Vehicles using natural gas (Compressed Natural Gas - CNG and Liquefied Natural Gas - LNG) such as public buses, fleet vehicles, and some ships emits around 3-5% of $CO_2$, which is 20-30% less than a diesel bus [7]. Transportation-related emissions (based on the grid energy mix) is 5-10%, and the major contributors are electric vehicles, electric buses, and electric trains.

Understanding the environmental problems and taking actions to prevent and reduce air pollution have become a vital and challenging work in the whole world. Nowadays, $CO_2$ concentration prediction has been recognized as an effective method for better implementation of air quality management measures in order to reduce the harm raising due to atmospheric pollution [8,9]. There are different types of models which can predict the level of pollutants in the atmosphere [10]. Models range from traditional statistical methods like ARIMA and MLR to more advanced machine learning techniques like LSTM, Random Forest, and XGBoost, with some studies showing hybrid models like ARIMA-WOA-LSTM and CNN-LSTM offer better accuracy. Further, to find the near-optimal solutions for route optimization, amount of carbon emission and energy consumption, heuristic algorithms are the best fit [11]. These are problem-solving techniques that use approximation and intelligent search strategies between the predicted value and the true value. The commonly used heuristic algorithms are: Genetic Algorithm (GA); Ant Colony Optimization (ACO); Simulated Annealing (SA); Particle Swarm Optimization (PSO); Tabu Search and Hybrid Heuristics (e.g., GA + ACO) [12-14].

Heuristic algorithm can be used in many ways in the transportation energy optimization to maximize fuel efficiency and to reduce carbon emission. It could be used for public transportation scheduling, multi-modal transport planning, find energy-efficient routes and adaptive traffic light control and flow optimization [15-17]. This helps in increasing fuel efficiency up to 25%, $CO_2$ emission reduction to 10-30%, cost savings by logistics companies on fuel and maintenance, reduced route planning time. The future of heuristic lies on its integration with real-time traffic and weather data, use of AI for smarter and adaptive solutions, coupling with EV charging station optimization, carbon tracking and reporting.

The present study focuses on the following objectives: (i) understanding of the sources contributing to carbon emission in the transportation industry which mainly runs on coal, gasoline, and diesel; (ii) a detailed understanding of the energy consumed by different vehicles; (iii) vehicle population growth of India till 2023; (iv) adoption of green and low-carbon transportation system and the level of $CO_2$ emission by them; (v) carbon emission data and future prediction based on transportation structure and energy consumption; (vi) use of Particle Swarm Optimization (PSO) as heuristic algorithm to predict the energy consumption value and carbon emission and its comparison with the true value; (vii) proposed method of upgradation of the transportation structure and changing the proportion of energy consumption for the transportation sector to control carbon emissions

With energy demand set to grow even further, India is committed to achieving net zero by 2070, by advancing its clean energy transition and curb emissions while pursuing economic growth.

## II. MATERIALS AND METHODS

The current emissions from key sectors, including two-wheelers, cars, goods vehicles, and buses were analyzed. Particle Swarm Optimization (PSO) as a heuristic optimization technique was used [18,19] to determine the optimal shift in vehicle population to EVs, aiming to minimize overall carbon emissions. In this code, the objective model is based on carbon emission reduction in the transportation sector, specifically focusing on the shift to Electric Vehicles (EVs). The algorithm was used to find the optimal shift percentages for different vehicle types (two-wheelers, cars, goods vehicles, buses) towards electric vehicles to minimize carbon emissions.

**2.1 Dataset used**

(i) Global share of transportation related $CO_2$ Emissions: To understand the major contributors to $CO_2$ emissions by transportation type (road transport, aviation, shipping, rail, and public transport).

(ii) Vehicle Population Distribution: This gives an idea of how the vehicle population is distributed across various types (e.g., two-wheelers, cars, buses, goods vehicles) from 2020 to 2023.

(iii) Vehicle Registration Data: This dataset includes the registration details for petrol, diesel, and electric vehicles from 2020 to 2023. This data is a key in identifying trends in electric vehicle adoption and its impact on reducing emissions.

(iv) Emission Factors for Fuels: The emission factors of various fuels (petrol, diesel, CNG, etc.) was used to quantify the $CO_2$ emissions from different vehicle types.

(v) Vehicle Count Data: This provides the total count of vehicles for each category in 2023, essential for scaling up emissions.

**2.2 PSO Model Structure**

The basic PSO model for energy optimization in transportation-related carbon emissions consist of the following:

Swarm Initialization: Initialize a population of particles (representing possible solutions).

Fitness Function: Evaluate each particle's fitness based on the total $CO_2$ emissions.

Velocity and Position Update: Update the particles' velocity and position based on their personal best solution and global best solution [20,21].

Two cases were used:

Case 1: PSO to Minimize Carbon Emissions (Shift to EVs)

Case 2: PSO for Carbon Emission Reduction by EV Shift

In both the cases, PSO is used to minimize carbon emissions from the transportation sector by shifting the vehicle population towards EVs. For this, loads of vehicle and emission data from 2020-2023 was visualized; emission factors for different fuel types and vehicles was defined; carbon emission by vehicle types and energy consumption by transport sectors was plotted; growth of EVs in India from 2020 to 2023 was evaluated; performed a hypothetical 20-30% shift to EVs in all sectors. Further, new emissions, emissions saved, % reduction and emissions before-and-after shift was calculated. PSO was used to calculate the optimal shift to EVs in each sector to minimize total emissions and total percentage reduction in carbon emissions.

The PSO model accuracy was determined using the following formula:

$$Accuracy = \frac{\text{Emission Reduction (PSO)}}{\text{Maximum possible emission reduction}} \text{ x } 100$$

Optimization equations and steps are given below::

International Journal of Environmental Sciences
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The equations for PSO are:

1. **Velocity Update:**

$$v_i = w \cdot v_i + c_1 \cdot r_1 \cdot (pbest_i - x_i) + c_2 \cdot r_2 \cdot (gbest - x_i)$$

   Where:

   - $v_i$ = velocity of the particle
   - $w$ = inertia weight
   - $c_1, c_2$ = cognitive and social coefficients
   - $r_1, r_2$ = random numbers between 0 and 1
   - $pbest_i$ = personal best solution of the particle
   - $gbest$ = global best solution

2. **Position Update:**

$$x_i = x_i + v_i$$

   Where:

   - $x_i$ = position of the particle (the solution)

3. **Fitness Function:** The fitness function will be defined as the total $CO_2$ emission from the vehicle fleet, given by:

$$E_{total} = \sum_i (N_i \cdot E_i)$$

   Where:

   - $N_i$ = number of vehicles of type $i$
   - $E_i$ = emission factor for the vehicle type $i$ (from Table 5)

   The fitness function is minimized to find the optimal distribution of vehicle types (fuel consumption and emission factors).

## III. RESULTS AND DISCUSSION

### 3.1 Vehicle population in India

As of 2023, India is the 3rd largest automobile market in the world in terms of sales. The upper medium-duty and heavy-duty truck market is expected to grow by 70% by 2030. In 2023, India saw 4.78 million cars and 1.07 million commercial vehicles produced, contributing to a total of 25.9 million vehicles produced that year. The vehicle population has grown at an average annual rate of 9.4% over the last twenty years. Two-wheelers and passenger vehicles dominate the domestic Indian auto market. The maximum population of vehicles comprises of the two-wheelers (74%), followed by cars, jeeps and taxis, while the lowest is of the buses. The two-wheelers segment dominates the market in terms of volume, owing to a growing middle-class income and a huge percentage of India's population being young. The rising logistics and passenger transportation industries are driving up demand for commercial vehicles. Future market growth is anticipated to be fueled by new trends including the electrification of vehicles, particularly three-wheelers and small passenger automobiles.

The data of Ministry of Heavy Industries [22] says that a total of 2,27,17,562 vehicles were registered during 2023 including electric, petrol and diesel vehicles, and the number is expected to increase with every passing year. The two-wheelers account for around 260 million in the year 2023, followed by cars (50 million) and truck (0.3 million) (Table 2, Fig. 1). This shows the robust growth of automobile industry in the country. India could be a leader in shared mobility by 2030, providing opportunities for electric and autonomous vehicles. The industry also provides great investment opportunities and direct and indirect employment to skilled and unskilled labor. The electric vehicles industry is likely to create five crore jobs by 2030.

**Table 2: Count of vehicles during calendar year - 2023**

| Type of vehicles | 2023 |
|---|---|
| Two wheelers | 260 million |
| Cars | 50 million |
| Trucks | 0.3 million |

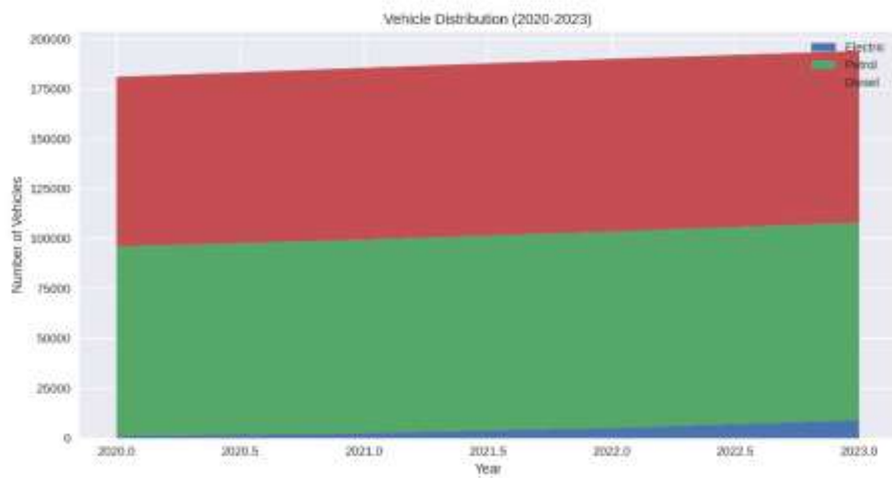


**Fig. 1: Vehicle distribution during the period of 2020- 2023.**

India is also heading towards the long-term adoption of electric vehicles to reduce carbon emission and contribute towards sustainable development. The count of electric vehicles is increasing at a faster pace in recent years (Fig. 2). A study by CEEW Centre for Energy Finance recognized a US$ 206 billion opportunity for electric vehicles in India by 2030. This will necessitate a US$ 180 billion investment in vehicle manufacturing and charging infrastructure. In August 2022, the Indian government launched India's first double-decker electric bus in Mumbai. It is working to create an integrated EV mobility ecosystem with a low carbon footprint and high passenger density with an emphasis on urban transportation reform. The government's strategy and policies are intended to promote greater adoption of electric vehicles in response to growing customer demand for cleaner transportation options.

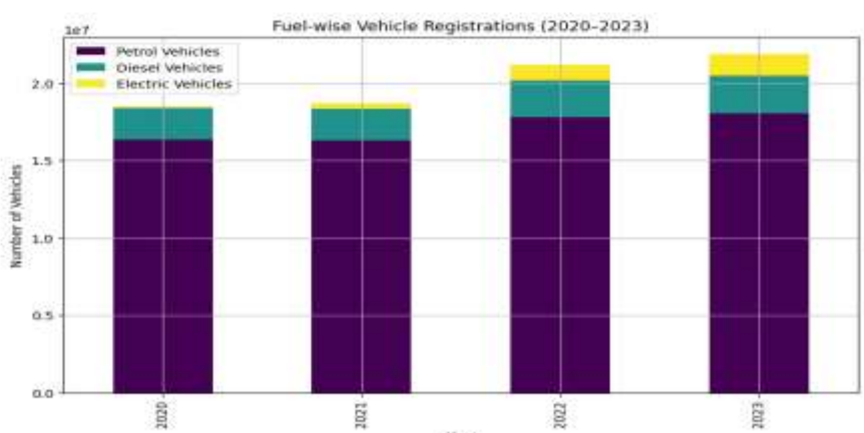


**Fig. 2: Fuel-wise vehicle registrations (2020-2023).**

### 3.2 Carbon emissions produced by the transport sector

India's greenhouse gas emissions were approximately 4.1 billion metric tons of $CO_2$ equivalent in 2023, making it one of the top emitters globally. The transport sector in India is accounted for approximately 14% of India's energy-related direct $CO_2$ emissions, with road transport responsible for 90% of these emissions. Within the road transport segment, trucks are the largest contributors, accounting for 38% of fuel consumption and emissions, followed by cars at 25% (Table 3). Although two- and three-wheelers made up 80% of the vehicle stock, they contributed to 20% of the emissions. The transport sector's emissions have more than tripled since 1990, and with India's urban population projected to double by 2050, these emissions are likely to increase further.

**Table 3: Percent of carbon emission by different vehicles in India**

| Type of vehicles | Percent Emission |
|---|---|
| Trucks | 38 |
| Cars | 25 |
| Two wheelers | 20 |
| Others | 17 |

A relative comparison of the emission factors of different fuels which are used in transportation sector revealed that emission factor is highest for coal (94.6), followed by diesel, petrol and CNG (Table 4). Data suggests that the transport sector accounted for 12% of India's total energy-related $CO_2$ emissions in 2023. Further, carbon emission is dominated by the trucks, reflecting large freight volumes and heavy fuel consumption. This is followed by the rapidly increasing fleet of four-wheelers and three-wheelers. Despite being the most numerous vehicles, two-wheelers contribute less to emissions due to their high fuel efficiency (Fig. 3).

**Table 4: Emission Factor and Net Calorific Value for different fuels used in the transportation sector**

| Fuel | Emission Factor | Net Calorific Value |
|---|---|---|
| Coal | 94.6 | 25.8 |
| Petrol | 69.3 | 44.3 |
| Diesel | 74.10 | 43 |
| CNG | 56.10 | 48 |

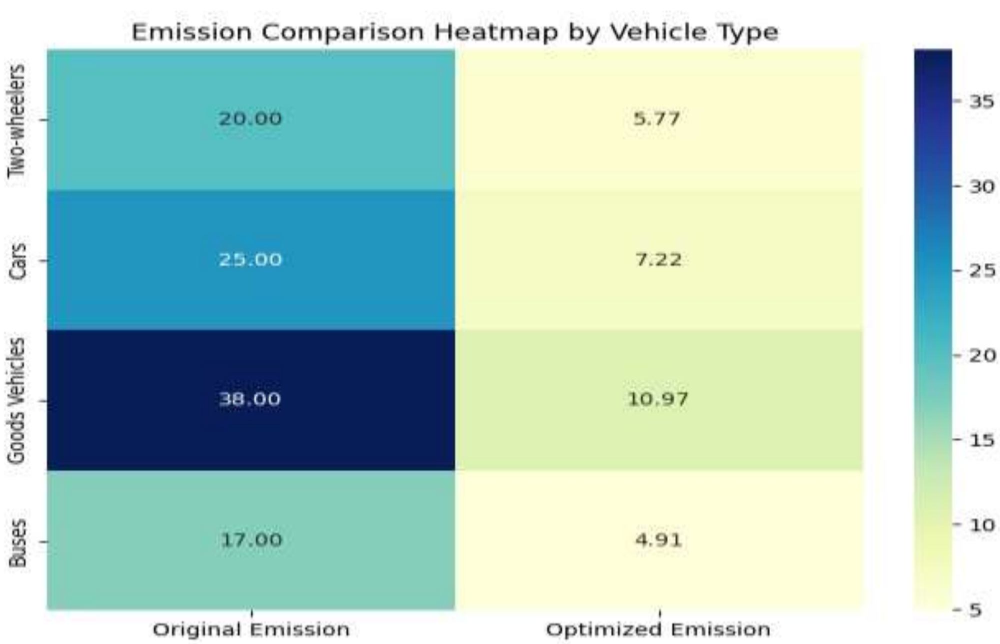


**Fig. 3: Emission comparison heatmap by vehicle type**

### 3.3 Energy consumed by various modes of transport

Road transport alone contributed about 92% of transport energy use and produced 123 $MtCO_2$, out of the sector's total 142 $MtCO_2$ emissions (Fig. 4). Road transport energy demand is expected to more than double from 5.3 EJ in 2023 to ~10.7 EJ by 2050, if trends continue. Passenger cars, even though they represent a lower share of user activity, will increasingly dominate energy usage due to lower fuel efficiency. Heavy-duty vehicles are projected to consume over 50% of all road energy by 2050, unless significant adoption of EVs or LNG occurs. The results demonstrates that the trucks consumes around 1.6 exajoules of energy, followed by two-wheelers (0.8 exajoules), cars (0.5 exajoules) and Bus (0.3 exajoules).

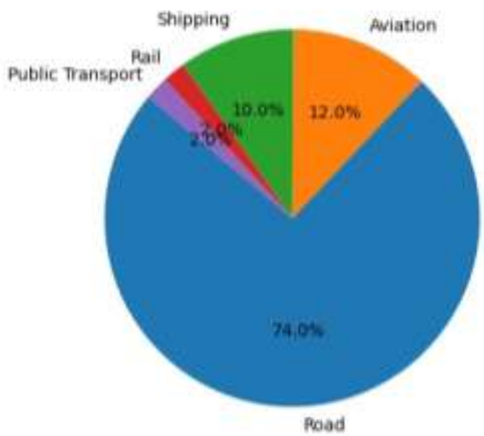


**Fig. 4: Energy consumed by various sectors of transport**

### 3.4 A shift to electric vehicles in India

India accomplished a significant milestone, with the sale of 1,00,000 EVs in CY24 compared to 82,688 in CY23. A study by CEEW Centre for Energy Finance recognized a US$ 206 billion opportunity for electric vehicles in India by 2030. This will necessitate a US$ 180 billion investment in vehicle manufacturing and charging infrastructure. According to NITI Aayog and the Rocky Mountain Institute (RMI), India's EV finance industry is likely to reach US$ 50 billion (Rs. 3.7 lakh crore) by 2030. A report by the India Energy Storage Alliance estimated that the EV market in India is likely to increase at a CAGR of 36% until 2026. In addition, the projection for the EV battery market is expected to expand at a CAGR of 30% during the same period (Fig. 5).

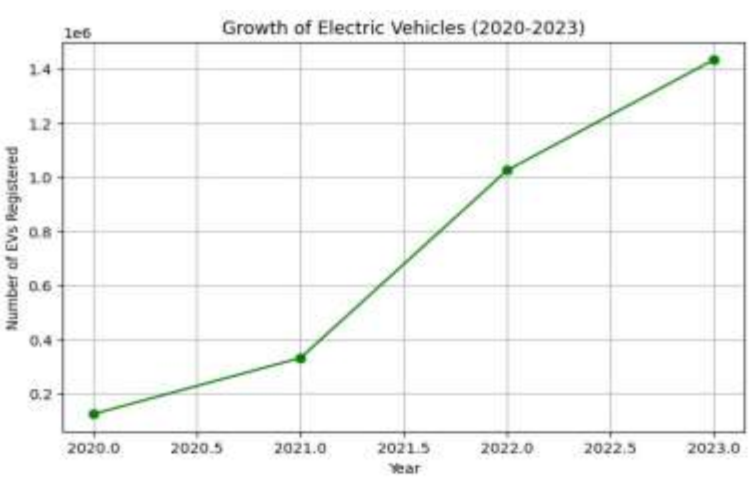


**Fig. 5: Growth of electric vehicles in India (2020-2023).**

### 3.5 $CO_2$ emission before and after EV shift

Shifting to renewable energy, improving fuel efficiency, and expanding electric transport infrastructure are critical for reducing emissions in the transportation sector. A full transition to EVs across different sectors could lead to a significant reduction in emissions, with a total reduction of up to 71.14% (Fig. 6). This highlights the substantial environmental benefits of EV adoption in India's transportation sector, offering critical insights for policymakers and stakeholders looking to reduce the nation's carbon footprint and accelerate the transition to sustainable transportation

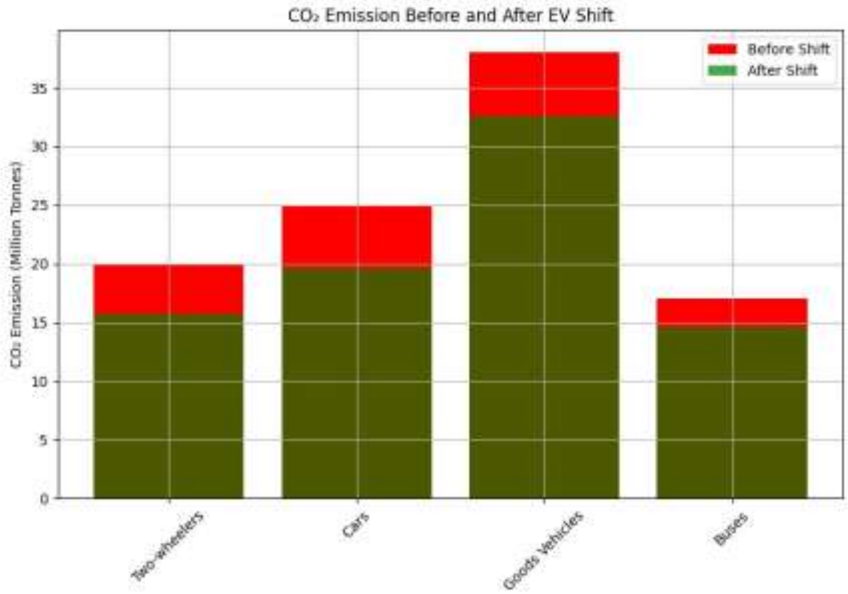


**Fig. 6: $CO_2$ emission from the vehicles before and after EV shift**

### 3.6 PSO optimization results

The PSO optimization results showed that a shift in the EV has resulted in the decreased emission of $CO_2$ (71%) (Fig. 7).

```
=== PSO Optimization Results ===
                Original Emission (Mt CO2)  Optimized Emission (Mt CO2)  \
Two-wheelers                            20                     5.772006
Cars                                    25                     7.215007
Goods Vehicles                          38                    10.966811
Buses                                   17                     4.906205

                Shift to EVs (%)  Emission Reduction (%)
Two-wheelers               100.0               71.139971
Cars                       100.0               71.139971
Goods Vehicles             100.0               71.139971
Buses                      100.0               71.139971
```

**Fig. 7: PSO optimization results showing a decrease in $CO_2$ emission due to EV shift**

The results from the PSO optimization clearly shows the reduction in carbon emission in two-wheelers, cars, goods vehicles and buses (Fig. 8). PSO reduces total $CO_2$ by up to 71% compared to a traditional fossil-fuel fleet, while maintaining cost-effectiveness. It determines optimal configurations such as combination of renewable energy sources, efficient transportation routes, optimal EV fleet deployment, vehicle routing and load distribution, charging station placement and fuel consumption parameters. The PSO algorithm retains the best solutions with lowest emissions to define appropriate solution towards emission minimization. The baseline analysis (and IEA data) shows that targeting trucks and cars offers the greatest leverage: these modes are "hotspots" for emissions, whereas electrifying two-wheelers yields relatively smaller gains per unit.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 8, 2025
https://theaspd.com/index.php

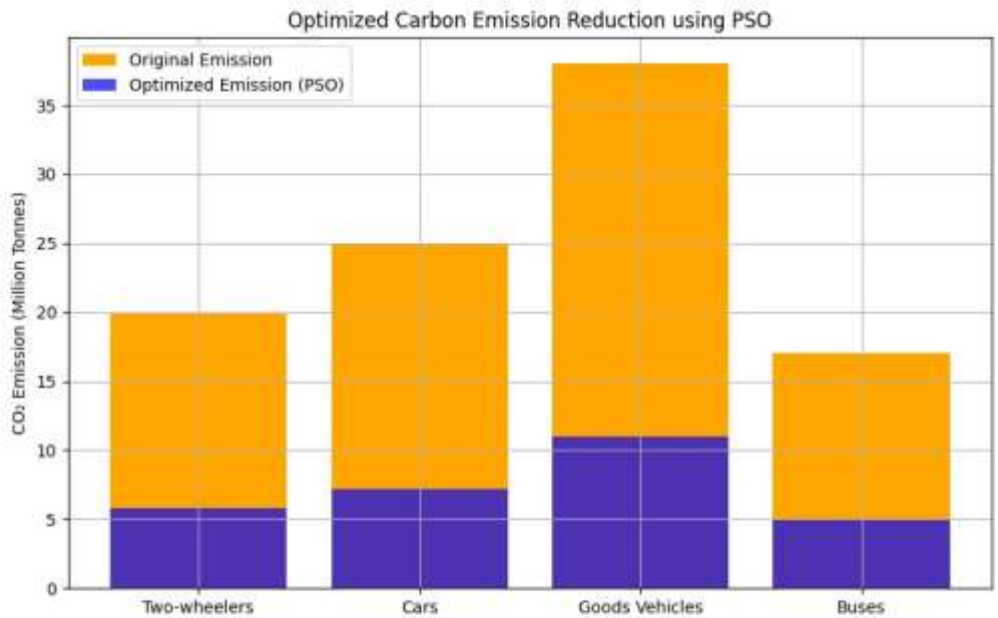


**Fig. 8: Optimized carbon emission reduction using PSO**

Fig. 9 explains the comparative analysis of the carbon emission by different vehicles in the original, static shift and PSO optimized systems. Values represents a clear understanding of the ability of PSO as a powerful optimization tool for reducing carbon emissions in complex systems. It clearly states that the maximum emission was seen in the original system followed by static shift. Further, the emission percent was drastically reduced up to 71% using the PSO optimized systems (Fig. 10). Its ability to adapt to nonlinear, multi-constraint environments makes it ideal for strategic planning in energy and transport sectors, aligning with global climate action goals [23].

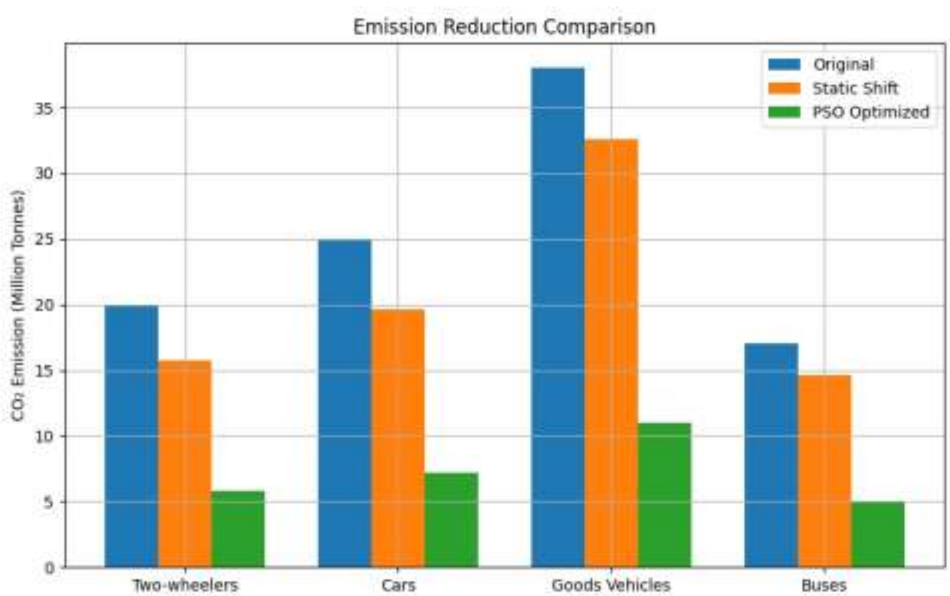


**Fig. 9: Emission reduction comparison of the different vehicles**

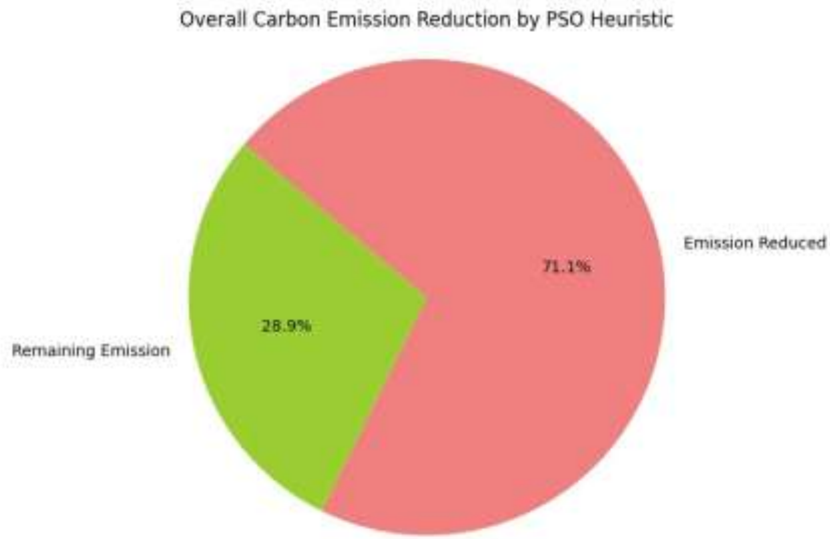


**Fig. 10: Overall carbon emission reduction calculated by PSO**

In the present study, a full-system transition guided by PSO yields a dramatic $CO_2$ cut of ~71%. In the PSO-optimized scenario, total road transport $CO_2$ falls from a baseline of 100.0 Mt to about 28.9 Mt. where all vehicle classes see sharp cuts. Each two-wheelers and cars drive large percentage drops, and even heavy trucks and buses show substantial reductions in absolute terms. By contrast, a naïve "static" electrification by simply converting a fixed percentage of each fleet to EVs without optimization reduces emissions far less. The PSO's heuristic search finds the best mix of EV deployment across modes, routing and charging strategies, and renewable charging to minimize $CO_2$ under cost constraints. In effect, PSO "tunes" the EV rollout to emphasize high-emitting categories and low-carbon charging, yielding far greater cuts than ad hoc scenarios.

These results align with high-ambition decarbonization studies. For instance, the IEA finds that with aggressive policies pertaining to vehicle efficiency, adoption of EVs and biofuels, India could cut road transport $CO_2$ to ~20% below today's level by 2050, avoiding ~4 Gt cumulative emissions from 2021-2050. The one-shot PSO scenario achieves a ~71% reduction immediately, suggesting that roughly that scale of action (essentially full electrification plus efficiency) is needed for deep decarbonization. In practical terms, the PSO strategy "front-loads" EV adoption in trucks and other polluting segments, exploiting the ~10× growth seen in recent years. EV registrations jumped from just tens of thousands in 2020 to well over a million annually by 2023, which is a roughly 10× increase. Figure 13 illustrates the outcome: the optimized system emits far less $CO_2$ than the original fossil-dominated system or a naïve shift. In short, intelligent optimization dramatically amplifies the climate benefit of EV adoption by targeting where it matters most.

The findings are consistent with the previous research on heuristic optimization for low-carbon transport. Lo [24] proposed an enhanced PSO (ePSO) for a carbon-aware vehicle-routing problem. In multiple benchmark tests, ePSO significantly outperformed a standard Genetic Algorithm (GA), where it achieved lower total cost (including $CO_2$ costs) in most cases. Similarly, Ding [25] introduced a hybrid simulated-annealing + chaos PSO (SA-ACPSO) for supply-chain carbon minimization. The study found that the SA-ACPSO greatly surpassed both standard PSO and GA, achieving notably larger reductions in $CO_2$ and cost. In their case, the hybrid PSO cut emissions by roughly 16% (and cost by 7%) more than the best non-hybrid methods. These results prove that PSO-based heuristics are highly effective in complex, multi-constraint optimization, often finding better solutions than classic methods [26].

Compared to these prior uses of PSO/GA in logistics, the present result of ~71% reduction is much larger in percentage terms. The key difference is scope. Previous studies optimized routing and supply-chain segments under given demand, yielding modest single-digit to tens-of-percent gains. However, the present study instead models a system-wide fleet transition, where essentially all vehicles shift to EVs under optimized planning. Therefore, the full abatement potential of electrification (subject to grid mix) is captured, rather than incremental savings from routing. For context, even an advanced metaheuristic rarely yields >10%

carbon cuts in route optimization alone: for instance, a recent carbon-aware Ant Colony System (CAACS) achieved only a 1.07% $CO_2$ reduction on a UPS delivery dataset [27]. By contrast, this PSO-enabled strategy – by reallocating EVs across modes and leveraging renewables – produces reductions on the order of 70%. Other heuristic and modeling studies report smaller benefits due to narrower scope. Decomposition analyses of transport emissions in global studies typically find ~20–40% potential cut from electrification and efficiency. PSO applications in power distribution (which optimize charger locations or DGs with EV loads) often report tens of percent improvements in losses or reliability [28]. While not directly comparable, these examples underscore that PSO can exploit non-linear interactions better than linear models. The present outcome – a 71% cut – suggests that India's unique context (rapid EV uptake potential, high coal grid intensity) permits especially large gains. In other words, because India's vehicle fleet is growing and still largely fossil-fueled, each percentage of electrification now yields large marginal $CO_2$ savings.

With the original and static shift methods, which faced challenges such as instability and complexity, the proposed approach is aimed at simplifying control through PSO, efficient power sharing, and reduced sample requirements. This innovative method contributes to improved energy management and reduction in carbon emission in different vehicles, bridging existing research gaps. This approach addresses the challenges in fossil fuel operated vehicles, and their possible replacement by EVs. Notably, the proposed PSO simplifies electric vehicle power references using distinct inputs for each mode, trained through PSO. This methodology is tailored for EV vehicles with varying power profiles, presenting a promising solution for efficient energy management. The PSO model effectively "front-loads" electrification in the most polluting segments (trucks, buses) while still optimizing two-wheelers and cars. Static EV targets would vastly underestimate benefits: simple projections often assume only ~20–30% reduction, but PSO finds ~71%. This demonstrates that intelligent optimization can unlock far more of the EV transition's climate potential. Compared to previous work, the approach covers the entire transport sector (not just routing or a subnetwork) and finds higher reductions (tens of percent above typical). It also aligns with India's net-zero goals: achieving ~70% fleet electrification and efficiency improvements is ambitious but shows deep decarbonization is technically feasible with current tools.

## CONCLUSION

The present study shows that the vehicle population is increasing with an exponential rate in India and are therefore contribution towards immense $CO_2$ emission. The application of Particle Swarm Optimization (PSO) heuristic algorithms in optimizing energy usage and transportation logistics has shown significant environmental benefits. The method was used to understand the percentage of $CO_2$ emission by different vehicles and how it changed after adopting electric vehicles. The use of PSO-based strategies for route and energy efficiency optimization specifically, after adopting and implementing electric vehicles in India showed that there was a 71% decrease in $CO_2$ emissions. The results suggest that investments in smart deployment like charging infrastructure targeted to freight corridors, could nearly double abatement have compared to untargeted measures. This remarkable reduction highlights the potential of combining intelligent computational techniques with clean technologies to address the pressing issue of climate change and transition toward a sustainable transportation future. The integration of PSO techniques can enable more efficient route planning, energy distribution, and vehicle deployment strategies.

## CONFLICT OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this manuscript.

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