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Smart parking and traffic congestion control using optimization

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Abstract

This research looks into the best ways to allocate parking spaces for vehicles with emission classifications in order to maximize riding and walking distances, petrol efficiency, and CO_2 emissions. The strategies examined are Conventional, Uncontrolled, Balanced, and Eco-friendly. This research presents an environmentally friendly method that uses the Artificial Bee Colony (ABC) Optimization and Whale Optimization Algorithm (WOA) to incorporate car emission classifications into the parking allocation system. The findings show that the Eco-nice strategy significantly reduces CO_2 emissions and fuel intake, outperforming alternative methodologies. It does this by reducing walking distances and altering the lengths at which electric powered vehicles (EV) and hybrid electric powered Vehicles (HEVs) are used. It performs admirably at parking occupancy prices as high as 60%; but, as costs rise, resource scarcity makes allocation increasingly challenging. The analysis also looks at how specific EV/HEV penetration rates affect how people use common spaces; it finds that, typical with sustainability goals, walking distances slightly increase while riding distances slightly decrease as these fees rise. The results demonstrate that the environmentally friendly approach simultaneously improves customer satisfaction and operational effectiveness and advances environmental sustainability in town parking areas. The results of the check indicate that a solid framework for realistic parking manipulation is presented by integrating modern optimization tactics like ABC and WOA with an eco-friendly approach, which reduces emissions and placement site visitor congestion in towns. This study provides helpful data on how to support future research to extend and improve these tactics to healthier multiple car classes and larger parking areas, so supporting significant efforts towards sustainable city improvement.

Keywords: Eco-friendly parking allocation, emission-classified vehicles, artificial bee colony (ABC) optimization, whale optimization algorithm (WOA), sustainability in urban parking, hybrid electric powered vehicles (HEVS).

Introduction

The rise of smart cities is a contemporary concern that utilizes state-of-the-art technologies to enhance the energy, transportation, health, and educational systems of society (Guevara and Auat Cheein 2020) [7]. The process of rapid urbanization poses both obstacles and opportunities, impacting several aspects such as infrastructure, transportation systems, and resources. Smart cities leverage technology and data to optimize urban living, making it more efficient, convenient, and environmentally sustainable. The objective of smart urban mobility is to establish transportation options that are more efficient, sustainable, and accessible for urban people, while simultaneously decreasing congestion and minimizing environmental repercussions (Tahir *et al*. 2023) [16] (Waqar *et al*. 2023) [17]. Nevertheless, the growth of urban traffic in recent decades has posed significant challenges for the management of transportation-related issues in smart city development. These issues include traffic congestion on road networks, availability of parking places, and environmental pollution (Paiva *et al*. 2021) [11], (Bakibillah *et al*. 2021) [3]. The increase in the number of cars during that same era has far surpassed the rise of the urban population in most metropolitan regions, resulting in significant issues. During the peak hour, the city centre has a parking demand for up to 30 to 50 percent of the overall traffic volume. If a driver is unable to locate a parking spot at the initial location, they often spend a period of time searching for it, which normally ranges from 3.5 to 14 minutes. (Hu and Wang 2018) [9]. As the car park becomes more crowded, it becomes increasingly difficult to find an available parking space.

The presence of cars circling in search of parking spaces contributes to the overall traffic congestion. Communication networks are an essential component of Intelligent Transportation Systems (ITS). Communication networks enable the transfer of information between cars, infrastructure, and control centers, which helps to optimize traffic flow and reduce congestion.

Locating vacant parking spaces is a prevalent problem in metropolitan areas because of the high volume of vehicles attempting to access consistently crowded zones. This exacerbates traffic congestion, fuel expenses, and the release of greenhouse gases (GHG) (Šolić *et al*. 2020) [15].

In addition, locating a parking space in an unregulated parking lot results in increased travel distance, walking distance, time consumption, and user dissatisfaction.

Hence, the parking management system remains an ongoing strategic concern that requires research efforts. It is crucial to include social and economic factors in order to establish a sustainable and environmentally friendly society (Chauhan *et al*. 2020) [4]. ITS, short for Intelligent Transportation Systems, encompasses a complex system of advanced technologies and solutions that are utilized for transportation and traffic management. Intelligent Transportation Systems (ITS) employ a range of components, including sensors, data connectivity, sophisticated algorithms, and real-time data processing, to enhance the efficiency, safety, and efficacy of transportation systems. Smart transportation encompasses the utilization of advanced technologies such as intelligent traffic lights, automated toll collection, GPS navigation, and other intelligent functionalities aimed at optimizing traffic flow and improving transportation services (Waqar, Othman, and González-Lezcano 2023) [18] (Waqar, Othman, and Pomares 2023) [19]. Intelligent Transportation Systems (ITS) have the potential to effectively improve the parking management system and address parking problems (Al-Turjman and Malekloo 2019) [1].

To get best environmental and operational results, this study emphasizes the requirement of adaptive parking management systems that fit different vehicle types and occupancy conditions. The goal is to investigate including more diverse car models and increasing the model's flexibility to real-time parking dynamics.

Parking management system

Parking Allocation Problem

A few years after reasonably priced cars were put into widespread production, there was a parking problem. Publications concerning the aesthetics of parking, pedestrian mobility, and safety can be found in good quantity starting in the 1940s. A car parking management system interfaces with an appropriate sensor network to monitor the occupancy of each parking space as well as pertinent data. It also has a decision system interaction mechanism for incoming vehicles. It is believed that a car will seek a parking space and provide pertinent information upon arrival. The management system then uses the decision algorithm or objectives to determine which available place is suitable.

Traffic jams and delays are decreased by effective parking management. The average amount of time US drivers took to find a good place to park was determined to be between 3.3 and 14 minutes by researchers. About 30% of all traffic was made up of drivers searching for a place to park (Mei *et al*. 2017) [10]. Transport engineers and urban planners face a dilemma from the growing demand for parking spaces. Planning for additional parking spaces usually backfires as the city's business activity picks up. These are well-known issues that were discovered in the past but haven't been resolved.

This paper presents a formal representation of the parking allocation problem by utilizing mathematical notations and equations to establish an optimal allocation system. Let K represent the set of all parking points. To simplify, we represent the collection of all parking spots as K, which is defined as the set of numbers $\{1, 2, \dots, N_k\}$, where each location is assigned a unique identification number. The availability of every parking point $k \in K$ is represented by ζK which can take the values of either 0 or 1. If $\zeta K = 1$, it means that the parking point is unavailable or currently occupied by a car, and vice versa. The minimum driving distance necessary from the entry to the exit for any parking site K is denoted as d_{drove}

$$d_{drove}(K) = d_{in}(K) + d_{out}(K) \tag{1}$$

where the distances to and from K are $d_{out}(K)$ and $d_{in}(K)$, respectively. The user must walk a distance of $d_{path}(K)$ to reach the establishment's closest entrance after parking their car there. For parking at K, the total walking lengths are therefore provided as

$$d_{walking}(K) = 2d_{path}(K) \tag{2}$$

The arriving cars are identified by their sequence number, $n = 1, 2, 3, \dots,$ and their arrival time, $t = \tau n$, corresponds to car n. Every vehicle notifies the parking management system with the pertinent Dn data and makes a parking spot request. The car's model $\mu n \in$ {EV, HEV, GV}, number of passengers ρn, and type $\delta n \in \{0,1\}$ are all included in the information $Dn \in \{\mu n, \rho n, \delta n\}$. In the event that a wheelchair or priority parking space is needed by any of the occupants in the car, $\delta n = 1$. Despite the wide range of car models available, we classify them into three main categories and refer to them as EVs (electric vehicles), HEVs (hybrid electric vehicles), and GVs (gasoline vehicles) because we can directly classify them based on the emissions they produce while parked. In the event that the parking allocation system's job is to choose an appropriate parking site $k \in K$ for car n at time t, subject to $\zeta K(t) = 0$.

Common plans for parking allocation

To better understand the underlying ideas and comparative notions of the eco-friendly optimal parking allocation system suggested in this research, we first examine a few common parking allocation schemes. While environmentalists anticipate that driving distance would be limited for lower emissions, most people want to park at the location with the least walking distance (comfort maximization). Taking into account these opposing factors, we first outline three potential baseline techniques.

- The conventional avaricious approach is assigning parking spaces close to the building's pedestrian entrance in order to reduce users' total walking distance and maximize user comfort.
- In the uncontrolled or random selection approach, parking spaces are distributed at random when a user comes and makes a request. An unregulated or stochastic distribution mechanism could potentially avert conflicts among users.
- The objective-balanced (just balanced) approach entails the equitable distribution of parking spaces based on the expenses associated with walking and driving.

Based on certain objective functions, the aforementioned (i) traditional and (iii) balanced techniques belong to the category of optimal parking selection systems. The process is simple: we define a weighted composite cost $J_{root}(pp)$ that includes the driving and walking distances needed to use a parking point pp for automobile x at time t.

$$J_{root}(pp) = wd_{drove} + (1-w)d_{walking}(pp) \tag{3}$$

Where ω is a trade-off factor that takes into account competing goals; that is, each phrase is equally stressed when ω = 0.5. Normalized distances $\bar{d}_{drove}$, $\bar{d}_{walking}$ are utilized in (3) instead of real distances since the ranges and fluctuations of the driving and walking distances of all parking spots are not identical. In particular, they are normalized to range from 0 to 1, or a maximum value of 1, as

$$\bar{d}_{drove} = \frac{d_{drove}(PP)}{dt_{\max}}, \forall pp \in P \tag{4}$$

$$\bar{d}_{walking} = \frac{d_{walking}(pp)}{wt_{\max}}, \forall pp \in P \tag{5}$$

Where the maximum driving distance is represented by $dt_{\max}$ = $\max_{pp} d_{drove}(pp)$) and the maximum walking distance is represented by $wt_{\max}$ = $\max_{pp} d_{walking}(pp)$ with $w = o$, the driving distance in (3) is disregarded in the case of the conventional (greedy selection) technique, and a parking site pp for $\varsigma_{pp}(t) = 0$ is chosen for automobile x arriving at t as

$$\min_{pp} J_{root}(pp)|\omega = o \tag{6}$$

It should be noted that the uncontrolled or random technique still outperforms the conventional greedy strategy since the latter may lead to numerous cars racing for the best parking space, which might ultimately result in additional expenditures for some of them.

Conversely, for an objective-balanced approach, a parking site p for $\varsigma_{pp}(t) = 0$ is chosen for automobile x arriving at t as the driving and walking distances in (3) are taken into consideration with a sufficient weight $0 \le \omega < 1$.

$$\min_{pp} J_{root}(pp)|\omega = \gamma \tag{7}$$

Where the constant γ is positive. Given the goal of reducing daily emissions and the average walking distance of all users, it is evident that the aforementioned conventional solutions have limits.

The role of base costs J_{root} as stated in (3) has several restrictions since it treats all vehicle types and user counts equally. In particular, as an electric vehicle (EV) emits no direct emissions, the term $\omega\bar{d}_{drove}(pp)$ referring to the environmental effect of vehicle emissions should differ depending on the kind of vehicle. Simultaneously, it is important to take into account the comfort of every user per automobile rather than only accounting for the walking distance of each individual user. These factors are taken into account in the suggested plan that is explained next.

Eco-friendly parking allocation system

Here, by further improving the optimization issue, we create an environmentally friendly parking allocation system to reduce CO_2 emissions in the parking facility for environmental sustainability while maintaining the general user comfort. In particular, we take into account the fact that GVs produce considerable emissions when parked in a closed space, whereas EVs and HEVs do not produce any direct emissions when operating at moderate speeds. Depending on the kind of incoming automobile, this information is appropriately quantified in the objective function and tuned accordingly. We take into consideration a convex objective function in the suggested system with regard to choosing a discrete parking site. Any exhaustive search algorithm with time complexity O(n) can solve the optimal issue. Therefore, the allocation problem can be resolved in a matter of milliseconds for a parking lot that can accommodate a few hundred to a thousand cars. With changes to(3), we add adaptive weighted prices that take into account the effects of car kinds and user numbers, as well as the walking and driving distances necessary to use a parking place p for automobile n arrived at time t

$$\begin{aligned} Jeco(p,n) &= \psi(n)\ \bar{d}_{drive}(p) + (1-\psi(n))\bar{d}_{walk}(p) \\ &+ \beta(\rho n - 1)\bar{d}_{walk}(p) \end{aligned} \tag{8}$$

Where ρn is the number of users, β is a constant or a factor to account for the additive cost for additional users in the car, and the adaptive trade-off factor $\varphi(n)$ of the car type is set as $w1, w2$ $(w1 < w2)$

$$\psi(n) = \begin{cases} w1 & if\ \ \mu(n) \in \{EV,\ HEV\} \\ w2 & \end{cases} \tag{9}$$

Here, the selection of $w1$ and $w2$ results in a partial mapping of the driving distance to the emission generated in the parking facility. In particular, $w1$ is selected to be less than $w2$ since EVs and HEVs don't emit direct emissions when driving at moderate speeds. The first word in (6), which reflects the automobile emissions attribute, partially accounts for the costs of the time and CO_2 emissions by the car needed to go the distance. The balancing cost of discomfort resulting from walking from the parking space is the second term in equation (6).

For autos with multiple users, a third term is inserted to account for additional expenses related to their discomfort when walking.

Based on the above considerations, in the proposed eco-friendly allocation scheme, a parking point p is selected for car n arrived at t as

$$\min_{p} Jeco(p,n) \tag{10}$$

Subject to (7) and $\zeta p(\tau n) = 0$.

With appropriate parameter tuning, the instant (non-predictive) status-based optimization is expected to provide an optimal solution that reflects the overall cost function minimization for a day-long operation in this parking allocation scheme for successively arriving cars of different types and varying numbers of users.

Background

Artificial Bee Colony (ABC) Optimization

ABC's mechanical bee hive contains three distinct species: resorted to the use of bees, which are tasked with finding specific food sources; observer bees, scout bees, who hunt for food sources at random, and worker bees, who watch the utilized bees dance around the hive to choose a food source, are examples of the former. Observers and observers are commonly referred to as jobless beekeepers since they are unemployed. Initially, it is up to the scout bees to locate all sources of food.

Here is how the ABC algorithm often works(Awais Ahmad a, Murad Khan b, Anand Paul c, Sadia Din c, M. Mazhar Rathore c, Gwanggil Jeon d 2018) [2]:

Initialization phase

The scout bees set the control parameters and initiate the population of food source vectors (m=1....SN, SN:). Each nutrient source, denoted by, represents a vector solution to an optimization problem where the objective function is minimized by optimizing a set of an independent variables, denoted by (Shan Jiang a, Jiannong Cao a, Hanqing Wu a, Kongyang Chen b c 2023) [13], It's possible to use the following definition while setting things up:

$$y_{mx} = l_x + rand(0,1)*(u_x - l_x) \tag{11}$$

Employees Bees Phase

Utilized bees will seek out new food sources close to those they've previously visited and remembered providing a higher concentration of nectar. They look around the area for food sources and assess their viability (fitness). (Dikshit, Sengupta, and Bajpai 2023) [6] They may, for instance, use the formula that is included inside the equation in order to discover a food source that is situated in the immediate area:

$$\upsilon_{mx} = y_{mx} + f_{mx}(y_{mx} - y_{kx}) \tag{12}$$

Where is a randomly chosen food source, is a parameter index determined at random, and is a randomly chosen integer between and [-a, a]. After establishing fitness, a greedy selection is made between it and existing food source. The formula below may be used to calculate the fitness value of the solution for minimization problems.

$$fit_m(\vec{y}_m) = \begin{cases} \dfrac{1}{1+f_m(\vec{y}_m)} & \text{if } f_m(\vec{y}_m)^3 0 \\ 1+abs(f_m(\vec{y}_m)) & \text{if } f_m(\vec{y}_m)<0 \end{cases} \tag{13}$$

Onlooker Bees phase-

There are two categories of bees who are unable to find work: onlooker bees and scout bees. Using the term presented in equation, you can compute the probability value with which an observer bee chooses.

$$p_m = \frac{fit_m(\vec{y}_m)}{\sum_{m=1}^{SN} fit_m(\vec{y}_m)} \tag{14}$$

An observer bee picks a food source at random, and then uses the equation to find a nearby source and assess its fitness. Between and, like the utilizing bee's phase, self-absorbed selection is utilized during this phase.

WOA Algorithm

The Whale Optimization programme (WOA) is an optimization programme that is built on how humpback whales interact with each other and how they hunt. The WOA programme tries to find food in the water like humpback whales do. In the WOA algorithm, a point vector in the search space is used to show each possible answer. The algorithm starts with a group of possible answers that are generated at random from the search field. A possible solution's quality is judged by how well it answers the optimization problem (Siahmarzkooh and Alimardani 2021) [14]. This is done with a fitness function. The algorithm works by going through several steps called iterations. Each iteration has three main steps: Search, surround, and bubble are all options. During the search stage, the position of each feasible solution is modified such that it is closer to the best answer identified so far. (Chowdhury, Mayilvahanan, and Govindaraj 2022) [5]. This step is a simulation of how humpback whales look for food. They do this by following the best available signs.

The WOA algorithm has been shown to be effective at solving a wide range of optimization problems, such as those in engineering design, data mining, and machine learning. The method is easy to use and only has a few settings that need to be tweaked. But, like other optimization algorithms, the WOA algorithm's success depends on the problem being solved and how the algorithm settings are set (Shakil 2019) [12]. So, to get the best results for a given problem, it is important to carefully tune the algorithm's settings (Haghnegahdar and Wang 2020) [8].

Table 1: Whale optimization algorithm

Algorithm 1 The Standard Whale Optimization Algorithm
Initialize a population of random whales
$W^* =$ the best search agent
$t = O$
While $(t <$ iterations)
for each whale
Update WOA parameters
and p)
if $(p < 0.5)$
if $(\|B\| < L)$
$W^{t+1} = W^* - B.Dis$
else if $(\|B\| \geq L)$
$W^{t+1} = W_{rand} - B.Dis$
end if
else if $(p \geq 0.5)$
$W^{t+1} = Dis'.e^{x.r}.\cos(2\pi r) + W^*$
end if
end for
Evaluate the whale W^{t+1}
Update W^* if W^{t+1} if better
$t = t + 1$
end while
return W^*

This work aimed to maximize walking and driving distances, fuel economy, and CO_2 emissions in urban settings by means of a hybrid ABC-WOA optimization technique to especially assign parking spaces for vehicles with varying emission categories. Including car emission categories into the parking allocation system allowed four strategies conventional, uncontrolled, balanced and environmentally friendly to be tested. Using the Artificial Bee Colony (ABC) Optimization and Whale Optimization Algorithm (WOA) to minimize CO_2 emissions and fuel consumption, our approach concentrated on the Eco-friendly strategy and so outperformed other strategies by reducing walking distances and optimizing the use of electric and hybrid electric vehicles (EVs and HEVs).

Table 2: Proposed Algorithm

Algorithm 1 Hybrid ABC-WOA Algorithm for Hyper parameter Tuning	
1.	Initialize parameters, hyper parameters, population for ABC and WOA
2.	While not convergence criteria met do
3.	For each solution in ABC population do
4.	Employ bee for exploration
5.	Evaluate fitness
6.	Update solution
7.	End for
8.	For each solution in WOA population do
9.	Update position using WOA equations
10.	Evaluate fitness
11.	End for
12.	Select best solutions from both ABC and WOA populations
13.	Update hyper parameters of VGG19 model
14.	Check for convergence
15.	End while

Result and Discussion

Figure 1 and 2 compares emission-classified cars' average walking and driving distances using the conventional, uncontrolled, balanced, and eco-friendly methodologies. With regard to the whole vehicle, the walking and driving distances for the balanced and eco-friendly approaches are about equal. This is because the Eco-friendly method's settings are adjusted to maintain constant overall average results. The walking lengths of EVs and GVs inside these cars, however, varied significantly using the balanced approach, the EV walking distance fell by 43.25% while the GV walking distance rose by 27.97%. Additionally, it's important to note that EV driving distance has grown by 23.50%, while GV driving distance has fallen by 15.62 percent. In contrast to other common optimization techniques, the Eco-friendly optimization method minimizes walking distance as a means of enhancing user comfort while slightly increasing the driving distance of EVs (or HEVs) compared to GVs to support an emission-free and fuel-efficient environment in the parking space.

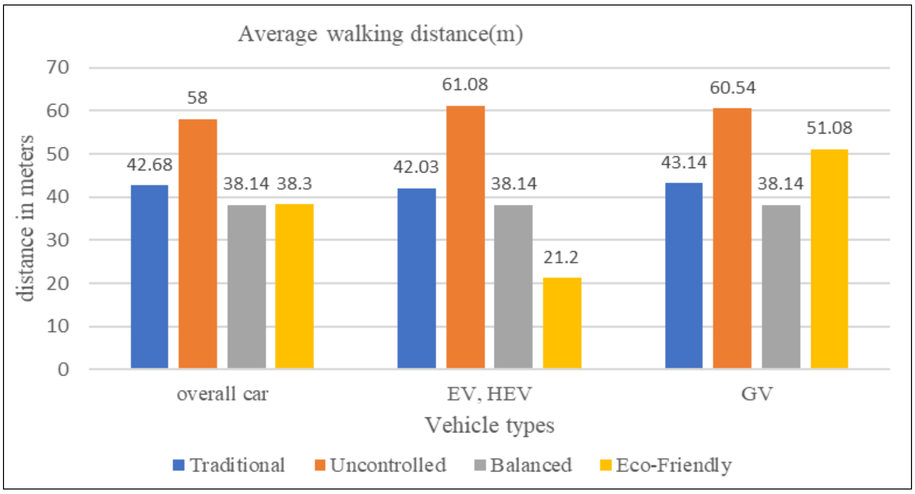

Fig 1: Average walking distance

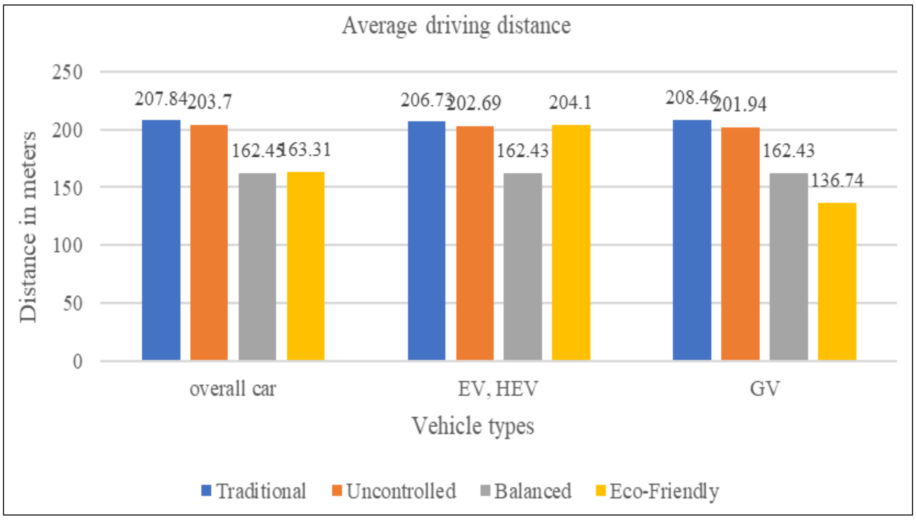

Fig 2: Average driving distance

Table 3 compares the typical fuel consumption and CO_2 emissions of cars using the Traditional, Uncontrolled, Balanced, and Eco-friendly approaches.

The results indicate that the suggested environmentally friendly approach reduced vehicle fuel usage and CO_2 emissions far better than other conventional parking allocation techniques. More precisely, the suggested environmentally friendly approach lowers car CO_2 emissions by 16.66%, 24.06%, and 28.22% as compared to the Balanced, Uncontrolled, and Traditional approaches, in that order. Similar decrease in fuel use results, and with it, corresponding savings in fuel costs. These performance increases are possible since the suggested eco-friendly approach took emission-classified vehicle types into account during the optimization process.

Table 4: Comparison of total CO_2 emission and fuel consumption of emission in a day

Driving Mode	Total CO_2 Emission (kg)	Total Fuel Consumption (l)
Eco-friendly	85.44	35.56
Balanced	102.10	44.35
Uncontrolled	110.04	46.16
Traditional	113.66	52.35

Based on the parking facility's occupancy percentage when the cars arrive as shown in Figure-3 we compute the average walking and driving distances. The average walking and driving distances at occupancy rates above 60% are found to be greater than the average daily distance travelled by all cars. This suggests that as occupancy rates get close to their maximum, it will become more difficult to allocate parking with comparable incentives for all users because there won't be as much space available. The suggested Ecofriendly model produces noticeably better results than any other model, and it may prolong maximum benefits up to 60% occupancy. Keep in mind that the model must choose from the few options available from the remaining sites (even if they are in the poorest category) when the best spots (with the least amount of driving or walking) are already taken. Keep in mind that no parking allocation method can guarantee a very pleasant space in the event of a limited availability; in the event of a 100% occupancy, the automobile will have to wait a long time in line.

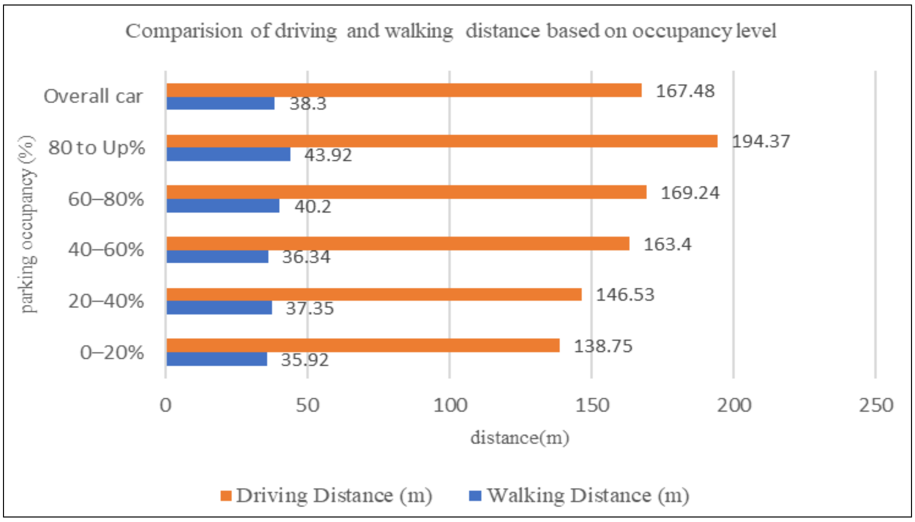

Fig 3: Average vehicle driving and walking distances determined by the parking space's occupancy percentage (%)

Lastly, we examine how well the eco-friendly approach that has been suggested performs for varying EV (or HEV) market entry or penetration rates. In particular, the walking and driving distances are produced using the same numerical simulations as before, and the arrival rates of EVs (or HEVs) fluctuate from 20% to 100%, with a step of 20%. Next, as seen in Table 5, the average walking and driving distances for EVs (or HEVs), GVs, and total automobiles are computed. With the penetration rates of EVs (or HEVs), it is discovered that the average walking distance for GVs and EVs (or HEVs) steadily rose, while the average walking distance for all automobiles gradually dropped and average driving distance for GVs and EVs (or HEVs), on the other hand, fell progressively with the penetration rates of EVs (or HEVs), as shown in Table 6, but the average driving distance for other automobiles climbed gradually.

Table 7: Average driving and walking distances of the cars for different EV (or HEV) arrival rates in the study parking lot.

Number of EV, HEV (%)	EV, HEV		Overall car		GV	
	Average walking distance	Average driving distance	Average walking distance	Average driving distance	Average walking distance	Average driving distance
0-20	20.12	205.95	41.77	161	47.59	146.4
20-40	22.072	202.8	38.97	163.86	48.65	138.95
40-60	23.89	201.65	35.41	169.01	52.62	124.92
60-80	26.59	193.06	31.91	179.61	61.02	109.75
80-100	29.17	181.32	28.92	181.9	-	-

The impact of the suggested eco-friendly approach on average fuel consumption and CO_2 emissions for different EV (or HEV) penetration rates in the study parking area is shown in Figure 4 and 5 Figure. As the use of EVs (or HEVs) grew, it was discovered that the suggested eco-friendly approach considerably decreased fuel usage and CO_2 emissions. As a result, putting into practice the suggested eco-friendly strategy based on vehicle kinds with emission classifications may greatly improve environmental sustainability within a parking area. Be aware that the size and features of the engine might affect the emission levels of non-eco automobiles (GVs). Other types of GVs are not taken into account in this research. These GV categories, however, may be included in the suggested scheme.

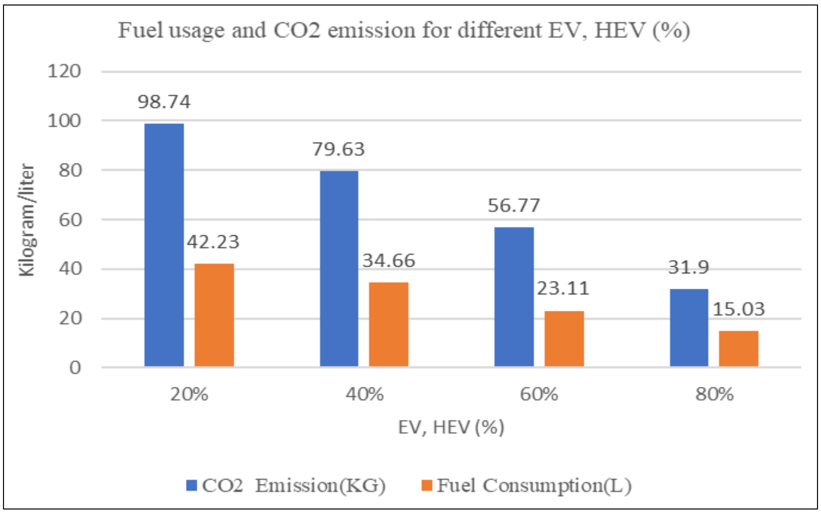

Fig 4: Impact on average fuel consumption and CO_2 emissions for different rates of EV (or HEV) penetration in the study parking lot.

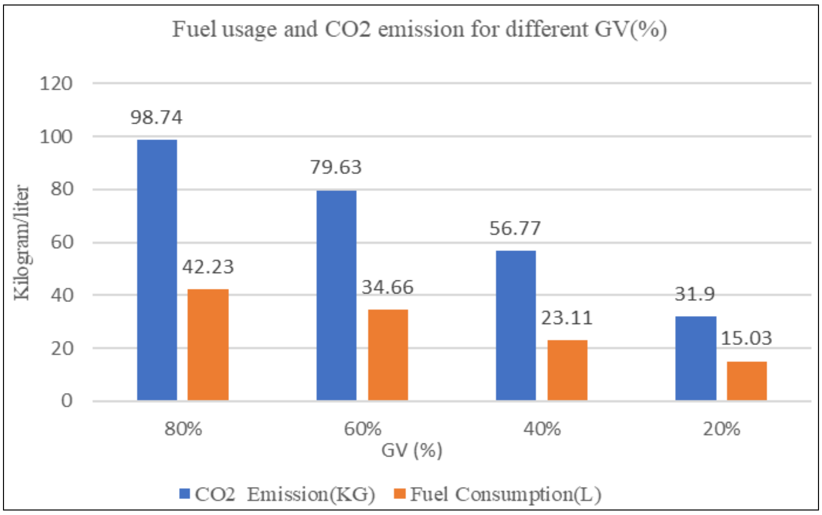

Fig 5: Impact on average fuel consumption and CO_2 emissions for different rates of GV penetration in the study parking lot.

Conclusion

The Eco-pleasant parking allocation technique, which makes use of Artificial Bee Colony (ABC) Optimization and Whale Optimization Algorithm (WOA), demonstrates superiority over Conventional, Uncontrolled, and Balanced techniques in optimizing parking operations by way of lowering bodily distances, fuel intake, and CO_2 emissions. This method integrates car emission classification to provide a tailor-made parking allocation that complements person delight and promotes environmental sustainability The Eco-friendly approach promotes emission-free and fuel-efficient environments in parking areas by mandating shorter walking distances and strongly promoting electric (EV) and hybrid electric vehicle (HEV) driving lengths. As the challenges of allocation become more pronounced when occupancy above this threshold, it becomes particularly interesting when occupancy rates reach up to 60%, so ensuring significant results as parking availability decreases.

The method's adaptability in unique penetration costs of electric vehicles (EVs) and hybrid electric vehicles (HEVs) further highlights its efficacy, as it was shown that average driving distances decrease while walking distances for gasoline vehicles (GVs) and electric vehicles (EVs) increase modestly as the proportion of these vehicles reaches higher levels. By prioritizing low-emission vehicles and optimizing their parking arrangement, this aligns with higher priority sustainability goals. Implemented using advanced optimization methods such as ABC and WOA, the Eco-friendly strategy establishes a solid foundation for managing urban parking facilities, resulting in improved operational efficiency and significant environmental benefits. Given its scalability and adaptability, this model is a viable option for reducing urban transportation congestion and pollutants. Therefore, more study and vigilance in this area could significantly enhance efforts towards urban sustainability.

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