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Optimal Charge Scheduling and Navigation for Multiple EV Using Deep Reinforcement Learning and Whale Optimization

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***Abstract*—The demand for Electric Vehicles (EVs) is increasing exponentially in recent times because of its ability to minimize energy savings and carbon emission. However, the charging process and charging option increases the challenges for EV adoption. With the growing adaptability to EVs, the need for addressing the challenges related to limited range and the availability of charging infrastructure becomes crucial. This paper presents an optimized deep learning-based charge scheduling approach in EVs for intelligent transport systems. The study leverages the Deep Reinforcement Learning (DRL) for making real-time decisions. The DRL model is trained using various features such as Battery critical percentage (SOC), time slots, nearest charge station, and availability of charging station. The features are optimized using a nature inspired Whale Optimization Algorithm (WOA), which helps in obtaining optimal charge scheduling. The proposed approach is experimentally evaluated in terms of reducing the tow counts in the selected region. Results from the experimental analysis validate the efficacy of the proposed approach in achieving optimal charge scheduling and navigation for EVs which also improve energy efficiency and reduce charging costs and charging time.**

***Keywords*—Electric Vehicles, Charge Scheduling, Intelligent Transport System, Particle Swarm Optimization, Whale Optimization Algorithm, Deep Reinforcement Learning.**

I. INTRODUCTION

THE ADOPTION of Electric Vehicles (EVs) is growing immensely for achieving environmentally friendly transportation by reducing the use of fossil fuel thereby contributing to the zero emission of toxic greenhouse gas [1]. Despite the advantages, the adaptability of EVs is restricted due to the challenges associated with the charging process such as limited charging stations, availability of charging slots, dynamic charging patterns, and varying load demand [2]. These factors contribute to the increase in the peak demand, grid overload condition, voltage fluctuation etc., which affect the performance efficiency of EV echo system [3] [4]. This inefficiency results in traffic congestion near the charging stations that impacts traffic planning, and traffic order [5]. This problem can be addressed by the intelligent transportation system wherein the details about the availability of charging station and time slot can be obtained beforehand. Several studies have focused on developing optimized charge scheduling mechanisms [6] [7] [8]. These techniques intend to avoid overload on the charging station during peak hours. However, most of these techniques calculate the charging time when EVs are either parked at home or parking lots. In practical scenarios, EV users require charging stations while driving (both shorter and longer durations) due to the limited capacity of EV batteries [9]. In this context, in real time, an efficient navigation mechanism is required to suggest optimal route and availability of charging stations for charging EVs considering different aspects such as distance, charging rate, and waiting time [10][11][12]. On this basis, a novel optimized charging scheduling framework for supporting multiple EVs is designed, developed and evaluated in this work. The prominent aspects of this manuscript are as follows:

- A feature extraction technique is employed to extract the relevant features related to the charge scheduling and a DRL based feature selector known as (DRLFS) is implemented for finding suitable features to improve the charge scheduling process.
- The selected features are optimized using a nature inspired WOA to obtain an efficient optimal charge scheduling in EVs.
- This framework efficiency is evaluated checking the number of tow count i.e., number of vehicles dead on the road before reaching its destination.

The rest of the paper is organized as follows. Section II discusses charge scheduling techniques presented in other works. Section III discusses the proposed charge scheduling framework in EV charging navigation for intelligent transport systems. Section IV briefs the simulation results and Section V concludes the paper with prominent future study observations.

II. LITERATURE REVIEW

A. *Utilizing Machine Learning*

Several machine learning techniques have been proposed for improving the overall efficiency of EV Charging echo system. The work presented in this paper [13] compares and evaluated the effectiveness of various machine learning (ML) approaches for EV charging considering conventional charging, rapid charging, and vehicle-to-grid (V2G) technologies. The work presented in this paper [14] provides the insights on the usage of machine learning models for determining the optimal location of EV charging stations (EVCS) and its infrastructure. Although from the mentioned references it is evident about the range of ML algorithms used in the EV charging navigation area, there summarize the need for looking into more advanced ML techniques, which is Deep Learning.

B. *Utilizing Deep Reinforcement Learning*

A subset of machine learning (ML), Deep Reinforcement learning (DRL) has attracted a lot of attention in this subject. Table 1 provides a summary of the areas of EV Charging echo system in which DRL is used.

Topical area: Advanced Artificial Intelligence in Applications

TABLE I. DRL USED STUDIES

Methodology & Focus	Reference
Deep reinforcement learning simulator to validate the feasibility of learning algorithms to be deployed	[15]
Deep-learning-based EV arrival rates calculated according to the historical data	[16]
Deep reinforcement learning for optimal scheduling of charging station according to the random behaviour characteristics of the EV charging arrival and departure times	[17]
Hybrid deep learning mechanism to assure safe and dependable charging operations that prevent the battery from being overcharged or discharged	[18]
Deep reinforcement learning based EV cluster scheduling strategy considering real-time electricity prices	[19]
Deep reinforcement learning to minimize the total charging time of EVs and maximal reduction in the origin-destination distance	[20]
Deep reinforcement learning based optimal charging strategy considering traffic conditions, user's behaviour, and the pricing	[21]
Deep reinforcement learning based evaluation of model-free coordination of EV	[22]
Deep reinforcement learning for EV charging navigation for single EV	[23]

C. Reseach Gaps

This research identifies some of the prominent research gaps from the existing works, which are outlined as follows:

In most of the existing techniques, the charging navigation estimations are not real time, which is required for making intelligent decisions for charge scheduling and navigation.

The most widely used deep learning used EV scheduling techniques has not ben verified for multiple EVs, which is required for measuring the efficiency of the EV charging echo system.

So, there is a need to investigate methods to enhance the adaptability of deep learning models to dynamic and uncertain environments, such as incorporating uncertainty estimation or developing RL techniques that handle real-time changes effectively.

III. PROPOSED RESEARCH METHODOLOGY

This research aims to develop an efficient DRL-based technique for charge scheduling and navigation in EVs to enhance overall power management and efficiency. In general reinforcement learning can learn from the actions and its continuous interactions from the external environment. This enables the reinforcement learning models to make fast decisions in a dynamic environment. In this research, the EV model itself is considered as the environment and the model learns the parameters of the EV such as the SoC of the battery, time slots, charging pattern and availability of charging station. The proposed charge scheduling strategy is designed to minimize the charging time, mitigate traffic congestion and improve the power management. In practical conditions, the driving cycle is more complex and DRL based control strategies help in finding the best solution for the complex problems aiming to achieve optimal charge scheduling.

The main goal of charge scheduling is to minimize the number of tow counts i.e., number of vehicles dead on the road before reaching its destination and also the power utilization of vehicles. Reduced number of tow counts is essential for achieving an optimal charge scheduling, which is also the aim of this research. In order to address the research gaps, the proposed DRL-WOA is designed which modifies the charging and scheduling process in real-time. This is achieved by optimizing model parameters which helps the system to dynamic environmental factors in an effective manner. In addition, the work also incorporates uncertainty estimation technique into the DRL framework to enhance the adaptability to uncertain environments. This integrated DRL-WOA approach enables continuous learning and adjustment based on real-time data, addressing the challenges of EV charging, scheduling, and navigation in dynamic settings.

The proposed work flow involved is shown in Fig. 1 and the same are explained in below subsections.

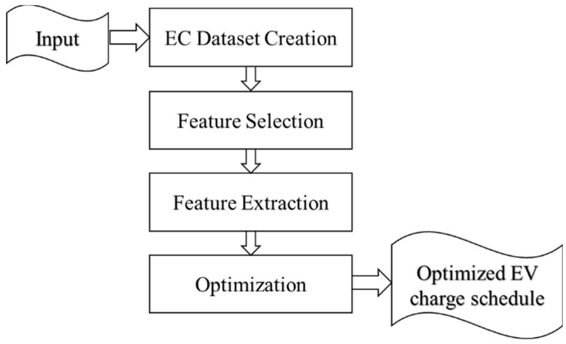

Fig. 1. Proposed workflow

A. EV Dataset Creation

In this study the data set is derived with random SOC, and at random coordinated within the city boundaries. To enable this, the following parameters are considered. Number of Vehicles, Number of Charging Stations, X Dimension of city (km), and Y Dimension of city. Based on these parameters, the EV Commute and Charging Station block set shall generate the dataset with the following data units such as Vehicle Number, Available battery Power, Needed Charging Time, Starting X-Position, Starting Y-Position, Destination X-Position and Destination Y-Position.

B. Feature Selction

In this step, feature selection is performed to select essential and relevant features from the dataset. It is important to perform feature selection in order to avoid the selection of irrelevant features. In this work, four important features are selected namely; (i) Time-Related Probabilities (timprob) (ii) Charging Probabilities (chprob) (iii) Battery Critical Level (batt_crit) and (iv) Charging Stations Locations as these are crucial for charge scheduling.

C. Feature Extraction

The DRL based Feature Selector (DRLFS) is implemented to identify an optimal subset containing relevant features. The architecture of the DRLFS is shown in Fig. 2. The DRLFS employs a reinforcement learning mechanism with an agent and an interactive environment. The agent in the DRL environment employs a learning-based policy for identifying and selecting the attributes for performing a specific task. Here, the features are selected based on actions and computes the rewards for every action. For effectively searching the feature subset the DRLGS employs a random policy along with two other search mechanism which helps in controlling the balance between exploration and exploitation. Entire searching process for feature selection is segmented into multiple smaller segments wherein each segment incorporates a continuous and sequential process. In this process, the features are selected and are grouped into a separate subset. This process is continued till the DRLFS reaches termination. In addition, several iterations are performed in each segmentation and during each iterative stage, the agent in the DRL environment identifies one feature and determines its actions, provides reward and stores the action for future learning. In particular, after every iteration the DRLFS generates a decision based on the selected features and acts accordingly.

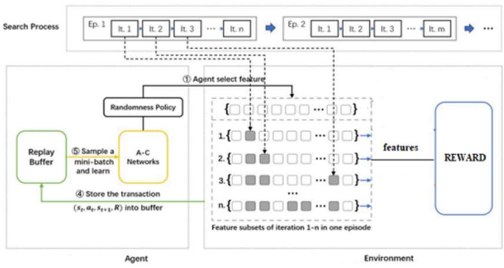

Fig. 2. Feature Selector

The proposed learning mechanism can be summarized as follows: Considering a search space 'S' wherein the feature set 'F' are randomly selected. In this work, the features are selected by computing a binary classification problem and hence is represented as $|S| = 2|F|$. Any change in the action of the DRL environment filters out certain important attributes and affect the correlation between them. In order to avoid this, each feature is reconfigured in the action space which in turn results in the formation of multiple discrete actions. However, it is a challenging and complex task to handle such a large action space since it affects the performance of the DRL in terms of making decisions about the feature selection process. In this context, this research considers a fine-grained action space in the continuous form as output. If the feature subset consists of only selected features then for every iteration, the DRL selects the features which belongs to the subset using a deterministic policy. After reaching termination, the feature subset obtained at the last iteration is considered as the final subset (Fe).

Let Error (F) and Error (Fe) represent the testing error for features F and final subset Fe, respectively. The objective is to obtain a minimum error and hence the reward function is computed as follows:

$$R = \text{Error (F)} - \text{Error (Fe)} \tag{1}$$

For the obtained error function, the maximum reward can be obtained by computing the optimal deterministic policy μ:

$$\mu* = \arg\max \mu \ \text{Error(F)} - \text{Error(Fe)} \tag{2}$$

For generating an optimal policy for feature selection, the DRLFS uses a Deep Deterministic Policy Gradient (DDPG) which is an off-policy actor-critic DRL algorithm. The DDPG uses a train and error method along with a stable, fine-grained action for training the DRL to find an optimal feature subset.

Pseudocode of the DRLFS algorithm
Initialization:
Randomly initialize critic network Q (s, α|θQ) and actor μ(s|θμ)
Initialize target network Q' and μ'
Initialize the Replay Buffer R
for episode = 0 to N do
Initialize the feature subset F as an empty set
Initialize the state s0 as a zero vector with a length d
while st is not se do
According to the current actor policy, select the action at = μ (s|θμ)
Randomize the action at by truncated normal distribution and decaying
Transform st to st+1 and add newly selected feature into F by at
Test the generalization error on the DRL algorithm and calculate the reward rt
Store the transaction (st, at, rt, st+1) into R
Sample a random minibatch from R
Update critic Q(s, α|θQ) by minimizing the loss
Update the actor policy μ(s|θμ) using the sampled policy gradient
Update the target networks Q' and μ'
if ≠ features = limit then
Set st = se
end if
end while
end for

In the DRLFS algorithm, each iterative step follows a criteria to terminate the current step and begin with another one. In this process, the selected features in the subset are defined as the search depth. In this research a fixed depth search (FDS) is considered by selecting a limited number of features. In the FDS, the searching mechanism in each iterative step terminates at a fixed depth. Such a policy provides a stable search evenly for every depth, which means that all different depths are explored for the same number of times. This helps in exploring more depth space and selecting more features. Further, the selected features are optimized to optimize the charge scheduling process in EVs, which is discussed in the next section.

D. Optimization

A Whale Optimization Algorithm (WOA) is used for further optimization of charge scheduling. The WOA is a metaheuristic technique which mimics the hunting behavior of humpback whales. The algorithm is inspired by the bubble-net hunting strategy. The humpback whales prefer to hunt schools of krill or small fishes that are close to the surface. This is done by forming bubbles across a circular path with 'upward-spirals' and 'double-loops'. Mathematically, the spiral bubble-net feeding maneuver is modelled in order to perform optimization.

WOA is mainly known for the hunting behaviour with the best search agent to chase the prey. The algorithm employs a spiral to simulate bubble-net attacking mechanisms of humpback whales. The stages involved in the algorithm are as follows:

Encircling Prey:

The algorithm assumes that the current best solution is close to target prey. Based on the obtained solutions, the position is further updated as shown in below given equations:

$$\vec{D}=|\vec{C}*\vec{X}\_best\ (t)-\vec{X}(t)| \tag{3}$$

$$\vec{X}(t+1)= \vec{X}\_best\ (t)-\vec{A}*\vec{D} \tag{4}$$

Where t defines the current iteration, A and C are the coefficient vectors, Xbest is the position vector of the best solution, and X indicates the position vector of the whales.

$$\vec{A}=2\vec{a}\,\vec{r}_1-\vec{a} \tag{5}$$

$$\vec{C}=2\vec{r}_2 \tag{6}$$

Where, vec{r1} , vec{r2} are random vectors in [0, 1].

Exploitation Stage:

This stage is also known as attacking mechanism of the Bubble net. This mechanism is mathematically modeled and involves two prominent mechanisms:

(i) Shrinking encircling mechanism: This behavior is achieved by decreasing the value of vec{a}, where a is decreased from 2 to 0 over the course of iterations.

(ii) Spiral updating position: In this process, the spiral position is updated with a random number that lies between -1 to 1.

Search for prey:

Humpback whales search randomly according to the position of each other

$$\vec{D}=|\vec{C}*\vec{X}_{rand}(t)-\vec{X}(t)| \tag{7}$$

$$\vec{X}(t+1)=\vec{X}_{rand}(t)-\vec{A}*\vec{D} \tag{8}$$

The pseudocode of the WOA is given below:

Initialization

```
Initialize the whale population Xi (i = 1, 2, …., n)
Calculate the fitness value of each search agent
      Xbest is the best search agent
while (t < maximum number of iterations)
        for each search agent
      update α, A, C, l and p
      if (p < 0.5):
      Update current agent using equation 3
else:
      Select the random agent Xrand
      Update current agent using equation 7
else:
      Update search agent using equation 4
end for
Check if the search agent crosses the search space
Calculate the fitness value of each search agent
Update Xbest if there is a better solution
t = t+1
end while
Return Xbest
End
```

The WOA leverages the selected features to generate an optimal charge scheduling plan, prioritizing charging sessions at times and locations where the distances to charging stations are minimal. This integrated approach ensures that EVs are charged in a manner that minimizes both time and distance, optimizing overall charging efficiency and user convenience. By optimizing the features, the optimal charge scheduling is generated, with a reduced number of tow counts, charging power, cost and time. The performance evaluation of this approach is discussed in the next section.

IV. Results And Discussion

The proposed DRL based charge scheduling approach is experimentally evaluated with respect to different evaluation metrics.

A. *Experimental Setup*

Based on the defined city dimensions, a EV data set is created. This data set is included in Table 2.

TABLE II. Base Config Data Set

Methodology & Focus	Reference
Number of Vehicles	20
Number of Charging Stations	10
X Dimension of city (km)	25
Y Dimension of city (km)	20

For navigation, this research identifies the details of the map locations which are tabulated in Table 3. Based on the map locations, the proposed approach simulates the map as shown in Fig. 3.

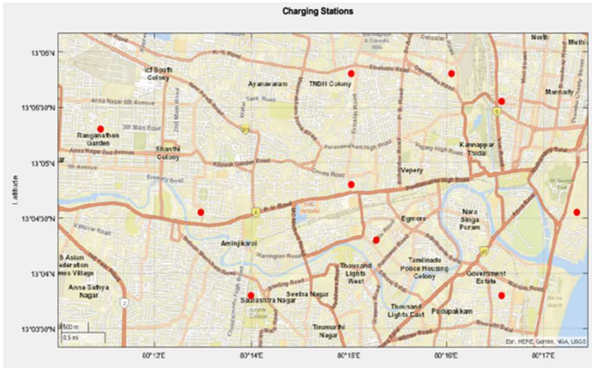

Fig. 3. Charging Station Locations

TABLE III. Charging Location Mapping

Locations	Simulation Map location (Latitude and Longitude)	Real Map locations (Latitude and Longitude)
1	(1, 1)	13.0859° N,80.2067° E
2	(3, 2)	12.9909° N, 80.2119° E
3	(4, 3)	13.0865° N, 80.2726° E
4	(-1, 2)	13.0698° N, 80.2245° E
5	(2, 2.5)	13.0853° N, 80.2607° E
6	(3.3, 4)	13.0938° N, 80.2891° E
7	(0.9, 3)	13.0629° N, 80.2314° E
8	(3, 5)	13.0732° N, 80.2609° E
9	(0, 3)	13.0696° N, 80.2728° E
10	(1.3, 5)	13.0806° N, 80.2876° E

With in this limits an EV charge scheduling dataset is created based on the features related to the charging station generator, charging station log, probability slabs, and EV generators the vehicle details with data required for validating the charging navigation which is included in Table 4.

TABLE IV. EV DATA SET

Vehicle Number	Available battery Power	Needed Charging Time	Starting X-Position	Starting Y-Position	Destination X-Position	Destination Y-Position
1	53	1.4	398	94	245	223
2	70	1.0	139	340	328	82
3	26	2.2	171	293	112	376
4	37	2.0	446	480	274	70
5	28	2.0	128	408	122	465
6	45	1.5	309	237	176	416
7	65	1.1	143	379	377	191
8	64	1.0	266	390	468	65
9	64	1.1	169	82	398	156
10	60	1.1	132	328	345	375
11	54	1.2	457	77	413	270
12	100	0.0	54	481	3	388
13	85	0.5	200	130	401	216
14	93	0.2	73	69	435	290
15	5	1.0	480	18	257	201
16	26	2.1	209	25	452	473
17	57	1.3	451	185	56	391
18	49	1.5	49	66	472	479
19	64	1.0	177	411	8	22
20	30	2.3	324	226	274	149

B. *Results*

The Tow count is the key output which is getting monitored between different stages. The stages which are getting monitored are represented in Fig. 4. For better charge scheduling the number Tow counts should be at minimal.

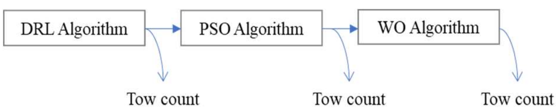

Fig. 4. Tow count computing stages

Using the generated data, initially, the performance of charge scheduling is determined without optimization. It was observed from the analysis that the total number of tow count vehicles without any optimization is 9. However, this number is too high and is not suitable for achieving appropriate charge scheduling. Hence the charge scheduling process is optimized using an existing particle swarm optimization (PSO) algorithm. Although PSO optimized results are better than the charge scheduling process without optimization, the number of Tow count vehicles is not completely minimized. The proposed WOA algorithm further minimize the Tow count vehicles. For the data set considered the Tow count got as zero. The result of the optimized charge scheduling is illustrated in Fig. 5.

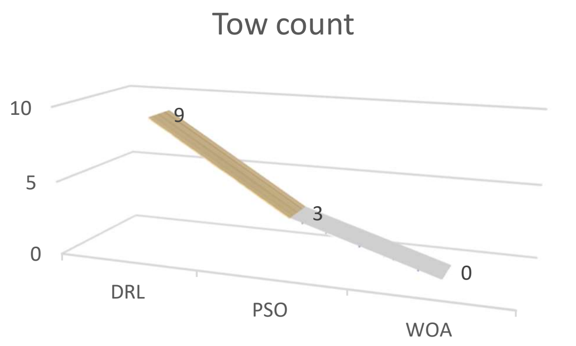

Fig. 5. Tow count values

As inferred from Fig. 6, the WOA algorithm achieves convergence in a lesser number of iterations and this shows that the features are optimized for the charge scheduling process

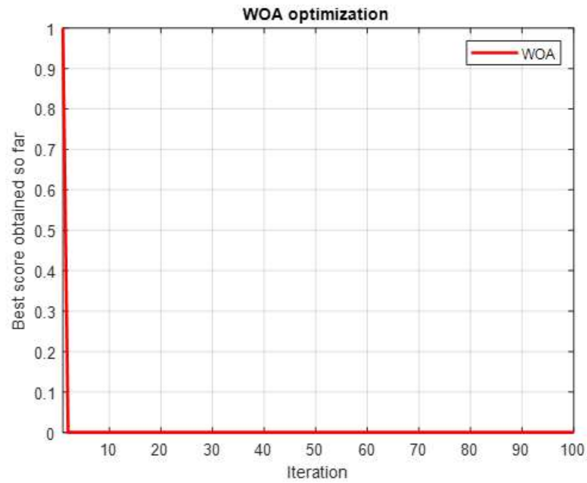

Fig. 6. WOA Iterations

Charge scheduling when the vehicle moves from one location to another with and without optimization is shown in below Fig. 7. In this its evident that the charge scheduling process is improved by also vehicle take the alternate routes. In addition, by improving the performance of the charge scheduling process the relative metrics such as average needed power, average charge cost, and average charging time also will be improved.

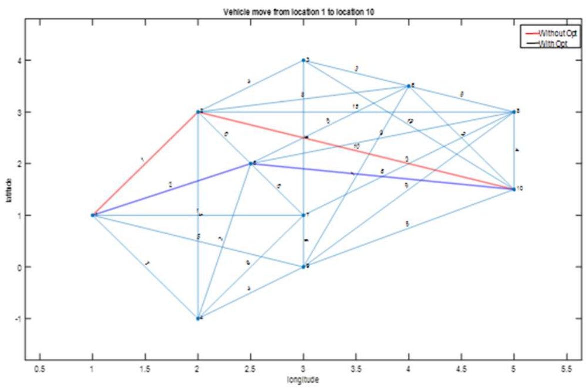

Fig. 7. Vehicle Navigation

Fig. 8 shows the implemented DRL based feature selector which selects the suitable features. This helps to reduce the overhead of analysing all features which inturn reduce the computational time.

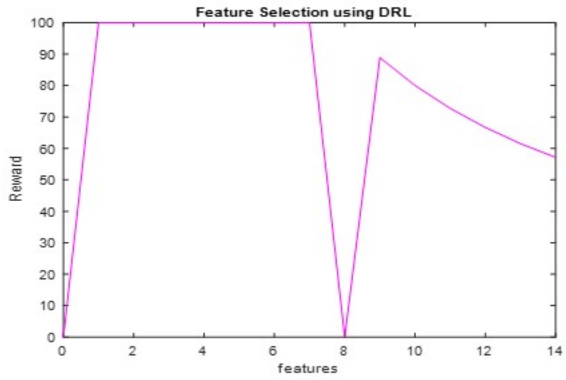

Fig. 8. Optimal Feature Selection

V. Conclusion And Future Work

The main aim of this research is to develop an efficient charge scheduling process for EVs to minimize the charging time and improve overall efficiency. An optimal EV charge scheduling approach is designed using an optimized DRL based framework. The proposed approach achieves an effective charge scheduling performance by selecting optimal features using the DRLFS technique. The efficacy of the DRLFS is evaluated in terms of effective feature selection which provides relevant features for optimizing the charge scheduling. The performance is evaluated without optimization and it was observed that the number of tow counts was high, which is not suitable for charge scheduling. Further, the features were optimized using the WOA, results show that the WOA reduces the number of tow count vehicles to zero in comparison to the existing PSO algorithm. In future, the study will be extended to evaluate the performance in a large city and with more vehicles.

Aligning to this, further exploration ought to focus on the below mentioned overlayered factors.

Integrate standardized protocols and interfaces: Evaluate the efficiency after integrating protocols and interfaces which are generally used with this frame work with diverse vehicle systems and components.

Safety and Validation: Evaluate this framework's capability to withstand the backdoor attacks which can be exploited to seriously harm the system components.

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