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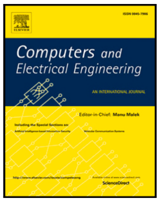

EVerGen: Optimal path planning for electric vehicle using modified genetic algorithm in internet of vehicular things

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ABSTRACT

The widespread adoption of *electric vehicles (EVs)* for green and eco-friendly vehicular systems, has brought several challenges, such as predicting the range in advance and selecting the optimal path with available charging stations. To address these issues, this paper proposes a novel routing strategy for EVs using a modified genetic algorithm and *edge computing based-Internet of Vehicular Things paradigm*. For an EV with low battery level, K-means clustering is used to select its present zone, and then the nearby charging point is traced. If the charging time is predicted, the user can search nearby amenities for refreshments. The range of the EV and the charging time are predicted using machine learning. Finally, an optimal path planning strategy is proposed using the modified genetic algorithm. By integrating real-time data from vehicles, charging stations, and traffic infrastructure, the proposed framework uses location-based services, optimizes the routing decisions, and anticipates charging requirements. The results demonstrate that the proposed strategy outperforms the existing strategies in terms of range prediction and charging time prediction. Using the proposed framework, the range can be predicted with >98% accuracy, and the charging time can be predicted with >98% accuracy. The benchmark results present that the modified genetic algorithm used in the proposed approach outperforms particle swarm optimization, ant colony optimization, and classical genetic algorithms. Furthermore, the use of multi-path-based optimal path planning outperforms the conventional single path-based approach in terms of travel distance, travel time, and energy consumption by ∼10%, ∼14%, and ∼11%, respectively.

1. Introduction

Optimal path planning is one of the significant topics in vehicular ad-hoc networks (VANETs). With the need to reduce carbon emissions and promote eco-friendly and sustainable mobility management, electric vehicles (EVs) have become a viable substitute for conventional internal combustion engine vehicles [1]. However, there are several obstacles in the general adoption of EVs,

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for the infrastructure for charging and limited range [2]. To overcome these obstacles, optimal path planning for EVs is on high demand to predict the range of the EV and provide the facility for selecting the nearby available charging station. The optimal path planning refers to the selection of the particular routing path of travel for an EV for which the objective i.e. minimization of travel distance, cost, or time is achieved. Furthermore, during charging of the EVs, the option of accessing other amenities or recreational facilities in the surrounding area is provided for the effective time utilization for the vehicular users. It is essential to use intelligent routing techniques and predictive models that can precisely assess an EV's remaining range and forecast how long it will take to charge for a particular trip. The vehicle parameters are determined by the expert's opinion, and the corresponding range is predicted using artificial intelligence (AI). For new vehicles, range prediction relies on Original Equipment Manufacturer (OEM) specifications. However, when used EVs are considered, then, the OEM models may not provide fruitful results because aging factors affect efficiency. The range prediction for used EVs is not OEM-specific due to variations in battery health and driving history. Instead, experts evaluate key parameters like battery degradation and past usage. These expert-driven inputs form the basis of an AI-powered range prediction model for EVs. The AI dynamically adapts to real-world conditions for more precise estimates, to ensure reliable range prediction, even for EVs with varying usage and maintenance histories.

Our goal is to improve the routing, range calculation, charging time prediction, and select the nearby available charging station for an EV in urban settings using the interconnection of vehicles, infrastructure, and communication networks. Using real-time data streams from vehicle sensors, charging stations, and traffic infrastructure, our suggested architecture provides fruitful decision-making for path planning and selecting the appropriate charging station. EVs powered by electricity from low-carbon emission grids offer substantial advantages in mitigating the climate impact associated with transportation and reducing the dependence of the transport grid on oil-based fuels [3]. EVs contribute to a cleaner and quieter environment while decreasing operating costs [4]. Plug-in EVs (PEVs) have also gained popularity by addressing the dependency on fossil energy and greenhouse gas emissions [5].

1.1. Motivation and contributions

A significant move towards the eco-friendly and sustainable transportation system has increased the popularity of EVs. Nevertheless, with the increase in the usage of EVs, several challenges arise, such as predicting the range in advance, selecting the suitable charging station, etc. Conventional methods for EV routing and selecting charging stations require a large amount of real-time data integration and dynamic adaptation capabilities. Conventional methods may result in an inefficient utilization of available charging resources and possible gridlock at charging stations. Innovative approaches for efficient EV routing and selection of appropriate charging stations across various locations are needed to address these problems. Integrating the Internet of Vehicular Things (IoVT) with edge computing can facilitate path planning. The motivation of this work is to provide an efficient EV routing strategy that will provide optimal path planning and efficient selection of charging stations. To address this objective, the authors' contributions are summarized as follows:

- An edge computing-based IoVT paradigm is proposed, where vehicles, roadside units (RSUs), and cloud servers communicate to facilitate the transportation system.
- An EV routing strategy is proposed using the modified genetic algorithm for real-time path planning based on the current vehicular data. Furthermore, an algorithm for selecting the nearby charging station is proposed. The proposed strategy is named *EVerGen* (*E*lectric *Ve*hicle *r*outing based on the modified *Gen*etic algorithm and machine learning).
- For EV range prediction, machine learning (ML) is used. The performance of various ML algorithms is analyzed to select the suitable one for range prediction with high accuracy.

The rest of the paper is organized as follows: Section 2 briefly illustrates the existing works. Section 3 demonstrates the proposed framework and the routing strategy. Section 4 presents the performance evaluation of the proposed scheme. Section 5 concludes the paper with directions for future work.

2. Related work

This section presents a summary of the existing works on routing in VANET with a focus on EV routing. In [6], the authors focused on improving the accuracy of EV range prediction, which is intricate due to numerous influential factors, including internal and external variables. The authors in [6], investigated how various factors, such as vehicle design, driver, and environment, create an impact on EV range. Based on the actual historical driving data, a hybrid ML model was proposed in [7] to forecast the remaining driving range of EVs. The Extreme Gradient Boosting Regression Tree (XGBR) and Light Gradient Boosting Regression Tree (LGBR), which are two cutting-edge ML algorithms, were combined to create the blended model. In [8], the authors proposed a method to forecast the remaining range of EVs and the minimal charge needed to complete a journey safely, using two recurrent neural networks (RNNs). In [9], a predictive control energy management system was developed for a light-duty range-extended hybrid EV powered by fuel cells. A cooperative speed forecasting approach based on the Markov Chain was suggested to meet the model predictive control framework. It consists of many predictive sub-models for managing various driving patterns. The authors in [10] proposed a novel path-tracking controller based on enhanced model predictive control with a Laguerre function and exponential weight created using a fully actuated-by-wire EV. In [11], the authors presented that while there is a growing interest in EVs, there is a lack of a structured approach to assess user experience.

Social networks, VANETs, and mobile edge computing (MEC) were integrated in [19] to introduce Social Vehicular Edge Computing (SoVEC) for the best possible route planning. In [20], the authors developed a mechanism for generating charging alert

Table 1
Comparison of proposed and existing approaches on EV.

Work	Contribution	Features						
		Meta-heuristics	Real-Time Path Planning	IoVT	Machine learning	Range Prediction	Charging Time	Edge Computing
Zhao, L. et al. [7]	ML-based EV range prediction	N	N	N	Y	Y	N	N
Zhou, G. et al. [12]	Meta-heuristic EV station optimization	Y	N	N	N	N	N	N
Yang, L. et al. [13]	Supervisory ML for EV monitoring	N	N	N	Y	Y	N	N
Raza, M. S. et al. [14]	IoVT-enabled automated EV framework	N	N	Y	Y	N	N	N
Zhang, Q. et al. [15]	Real-time route optimization	N	Y	N	Y	N	N	N
Ullah, I. et al. [16]	ML-based charging time prediction	N	N	N	Y	N	Y	N
Qiang, X. et al. [17]	Meta-heuristic route planning	Y	Y	N	Y	N	N	N
Bi, J. et al. [18]	Battery and charging behavior prediction	N	N	N	Y	N	Y	N
Proposed Approach (EVerGen)	Real-time path planning, range prediction, and charging time prediction for EVs in IoVT with edge computing	Y	Y	Y	Y	Y	Y	Y

Y: Yes/ considered/ performed, N: No/ Not considered.

and route planning for EVs with insufficient energy. In [21], an intelligent path planning approach was proposed by combining the power grid, dynamic wireless power transfer (DWPT), and urban electrified transportation network for every EV. In [22], the authors demonstrated an approach for managing the charging scheduling of EVs, with an emphasis on choosing a Charging Station (CS) that is appropriate for the energy-demanding EV. To minimize the operating costs, maximize power exchange profits, and ensure residential comfort levels of EVs, the authors in [23] assessed how consumer power exchange affects stakeholder costs and profits. In [24], a blockchain and game theory-based secure wireless charging scheme was proposed to ensure privacy and optimal energy scheduling, demonstrating improved utility and security. In [25], an intelligent vehicle-to-vehicle charging navigation strategy was proposed for many mobile EVs. A semi-centralized charging navigation framework was illustrated based on MEC via a hybrid VANET-based communication paradigm to ensure dependable communication and effective charging coordination. In [26], an overview of the implementation and administration of EV networks (EVNs) was presented, considering the energy flow, data communication, and computation aspects. The issue of EV charging information in VANETs and the decentralized distribution of vehicle-to-vehicle charging pairs were addressed in [27].

Though several approaches were explored for EV routing, accurate range prediction and selection of appropriate charging stations in a time-efficient and energy-efficient way are on demand. To address this objective, the proposed framework offers time-efficient and energy-efficient path planning with high accuracy for EVs. The comparison of the proposed strategy EVerGen with the existing approaches is presented in Table 1. In [7,13], and [16], the authors primarily focused on range prediction and charging time prediction but did not integrate IoVT and ML for real-time path planning, limiting their applicability to dynamic vehicular networks. In [12,17], real-time path planning was addressed. However, range prediction, charging time prediction, and edge computing were not considered [12,17], hence, potentially affecting efficiency in energy-constrained environments. In [14], ML was used for range prediction. However, real-time decision-making was not performed in [14], hence, reducing the effectiveness in connected vehicular networks. In [15], reinforcement learning was used for route planning and power management for plug-in hybrid EVs. In [18], EV charging time was predicted, but range prediction was not performed. The existing approaches did not consider the multi-path scenario, and user amenities during the selection of charging station. To address the limitations of the existing approaches, the proposed approach integrates IoVT, ML, and edge computing, to offer a holistic solution for real-time path planning. From Table 1, we also observe that the proposed approach is unique and has more features compared to the existing approaches on EVs.

The existing mobile applications available for vehicle routing provide path planning advises. However, it lacks essential features for EV path planning, such as charging station awareness and optimization based on battery levels. We consider location information, road traffic, and road type, along with the EV range, battery level, and charging station availability, for efficient and sustainable travel. Further, multiple objectives are considered in the proposed approach such as minimization of distance, cost, or time, during path planning. Using ML and IoVT, our system continuously refines routing for EVs. This ensures optimized energy use, minimal charging downtime, and improved trip planning.

3. EVerGen: Proposed EV routing strategy

In this section, we illustrate the process of EV range prediction, charging station-based clustering, modified GA-based routing, and path planning. The adoption of modified GA presents a compelling proposition for optimal path planning in EV networks within the IoVT framework. We consider a three-tier IoVT framework that contains the IoT devices attached to the vehicles used for data collection such as cameras, velocity predictors, etc., the vehicles, and the cloud servers, as demonstrated in Fig. 1.

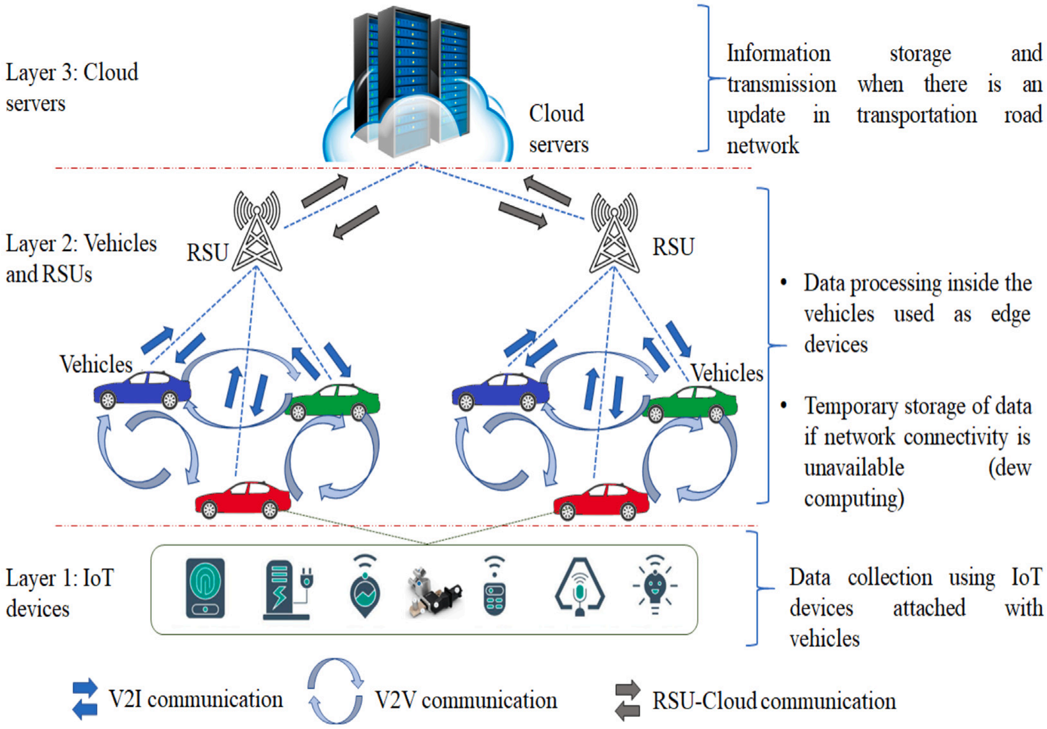

Fig. 1. Three-tier architecture of EVerGen.

In layer 1, the IoT devices are used for data collection. The collected data are analyzed inside the vehicles used as edge devices in layer 2. The vehicles are connected with the cloud servers at layer 3 through RSUs. In IoVT, vehicles can communicate with each other, referred to as vehicle-to-vehicle (V2V) communication, and vehicles can communicate with infrastructural components such as RSUs, which is referred to as vehicle-to-infrastructure (V2I) communication. In EVerGen, both V2V and V2I communications take place. As vehicles move, network connectivity becomes major issue. Hence, entire data analysis inside the cloud is a challenge. To overcome this problem, vehicles are used as edge devices, and they perform local data analysis using ML for predicting EV range, charging time, etc. The cache-based dew computing allows temporary data storage when Internet connectivity is unavailable. The synchronization with the cloud is also maintained. The vehicles further perform EV routing using modified GA, and optimal path planning. The information transmission to and from the cloud to vehicles take place whenever there is an update in the transportation road network to make the routing dynamically optimized.

3.1. Modified genetic algorithm (MGA)

The proposed Modified Genetic Algorithm (MGA) introduces adaptive mechanisms for better search performance compared to classical GA. MGA uses adaptive rank-based selection with elitism. The crossover is used for a diversity-preserving multi-parent strategy and feasibility correction, and mutation becomes self-adaptive and non-uniform, decreasing over generations. MGA also monitors population diversity using fitness variance to avoid premature convergence. MGA maintains a dynamic exploration–exploitation balance, enabling broader search early and stronger convergence later. Specifically, the proposed MGA incorporates (i) dynamic fitness adaptation, (ii) safety-aware multi-constraint encoding with variable-length chromosome representation, (iii) adaptive crossover–mutation probability control based on convergence rate, and (iv) risk-prioritized route repair mechanisms.

3.1.1. Fitness function

Each chromosome s represents a feasible route ($\mathcal{R}_s$) in the graph. The objective function fitness is defined as the minimization of distance, cost, and travel time as follows:

$$F(\mathcal{R}_s) = \alpha Distance(\mathcal{R}_s) + \beta Cost(\mathcal{R}_s) + \gamma Time(\mathcal{R}_s),$$

where $\alpha + \beta + \gamma = 1$, and $Distance(\mathcal{R}_s)$, $Cost(\mathcal{R}_s)$, and $Time(\mathcal{R}_s)$ denote total distance, cost, and travel time, respectively.

3.1.2. *Modified rank-based selection with adaptive pressure*

A generation-dependent and problem-specific selection is performed to improve the performance of the classical GA. Instead of roulette-wheel selection, MGA employs adaptive rank-based selection. If ξ_s denotes the rank of chromosome s (best rank = 1), the selection probability ($\mathcal{P}_{selection}$) is given as,

$$\mathcal{P}_{selection} = \frac{e^{-\kappa \xi_s}}{\sum_{p=1}^{P} e^{-\kappa \xi_p}},$$

where κ controls selection pressure and P denotes population size. The parameter κ increases gradually with generation g as follows:

$$\kappa^{(g)} = \kappa_{\min} + \left(\kappa_{\max} - \kappa_{\min}\right) \frac{g}{\mathcal{G}}.$$

where $\mathcal{G}$ denotes the number of generations. This ensures stronger exploitation in later generations while maintaining exploration initially. Additionally, elitism preserves the top η chromosomes as follows:

$$\mathcal{E}^{(g+1)} = \{\mathcal{R}_1, \mathcal{R}_2, \dots, \mathcal{R}_\eta\}.$$

3.1.3. *Diversity-preserving multi-parent crossover*

Typically, classical GA produces two offspring from two parents. In this study, we introduce a three-parent crossover mechanism to enhance the balance between exploration and exploitation. If $\mathcal{R}_1$, $\mathcal{R}_2$, and $\mathcal{R}_3$ are the selected parents, the offspring is generated as follows:

$$\mathcal{R}_{\text{child}} = \Pi\left(\mathcal{R}_1[1 : s] \cup \mathcal{R}_2[s : p] \cup \mathcal{R}_3[p : \eta]\right),$$

where $\Pi(\cdot)$ denotes feasibility correction ensuring no repeated nodes. The crossover probability ($\mathcal{P}_{cross}$) is adaptively adjusted using population diversity σ_F as follows:

$$\mathcal{P}^{(g)}_{cross} = \mathcal{P}^{\max}_{cross} \frac{\sigma^{(g)}_F}{\sigma^{\max}_F}.$$

Higher diversity encourages crossover, while lower diversity reduces disruption in later generations.

3.1.4. *Self-adaptive non-uniform mutation*

To focus on generation-dependent mutation to prevent premature convergence, MGA introduces self-adaptive mutation. The mutation probability ($\mathcal{P}_{mutation}$) decreases nonlinearly with generations as follows:

$$\mathcal{P}^{(g)}_{mutation} = \mathcal{P}^{\max}_{mutation} \left(1 - \frac{g}{\mathcal{G}}\right)^2.$$

Mutation is non-uniform and position-sensitive as follows:

$$\mathcal{R}'_s(g) = \begin{cases} \text{Random feasible node}, & \text{if } u < \mathcal{P}^{(g)}_{mutation}, \\ \mathcal{R}_{mutation}(g), & \text{otherwise}, \end{cases}$$

where $u \sim \mathcal{U}(0, 1)$. Early generations promote exploration, while later generations refine solutions.

3.1.5. *Diversity control via fitness variance*

Population diversity is monitored using fitness variance as follows:

$$\sigma^{(g)}_F = \frac{1}{P} \sum_{p=1}^{P} \left(F_p - \bar{F}\right)^2.$$

If ϵ denotes the convergence threshold, and $\sigma^{(g)}_F < \epsilon$, a partial population re-initialization is performed as follows:

$$P'^{(g)} \leftarrow \mathcal{E}^{(g)} \cup \text{Random}(P - \eta),$$

to prevent stagnation and maintain global search capability.

3.1.6. *Convergence property*

Due to elitism and bounded fitness, the best solution satisfies ensuring monotonic improvement, presented as follows:

$$F^{(g+1)}_{\text{best}} \leq F^{(g)}_{\text{best}},$$

The adaptive crossover–mutation balance provides global exploration initially and local exploitation later, improving convergence speed and solution stability compared to the classical GA.

Table 2
Mathematical notations used for EV charging location clustering and routing.

Notation	Description
X	Matrix of predictor variables
X^T	Transpose of the matrix
D	Set of m EV charging station data points
C	Clusters
μ	Set of cluster centroids
μ_i	Centroid of cluster C_i
V	Set of vertices of graph G
E	Set of edges of graph G
$dist_{ij}$	Distance between v_i and v_j
$cost_{ij}$	Cost associated with traveling from v_i to v_j
q_i	Energy demand at v_i
Q	Maximum capacity (energy) of the EV
ζ_0	Initial energy level of the EV
ζ_{min}	Minimum threshold level of energy of the EV required to travel
t_{ij}	Travel time between v_i and v_j
ϕ_i	Occupancy status of the charging station at v_i
$T_{\max}$	Maximum allowable travel time for the EV

3.2. EV range prediction

EV range prediction based on vehicle characteristics is essential to effectively plan the journeys. The EV range is predicted in terms of distance. The parameters such as model, rated power, maximum (max) power, top speed, battery capacity, charging time, and range play crucial roles in estimating the range of an EV. Based on these parameters, the drivers can be guided with an accurate estimation of how far they can travel on a single charge. The rated power and max power values help to assess the motor's efficiency and energy consumption during various driving conditions, while the top speed influences aerodynamic drag and energy usage. The battery capacity is crucial, representing the total energy available for driving, and charging time has an effect on trip planning. Real-world variables such as driving behavior and environmental conditions are considered to ensure reliable range predictions for drivers, thereby addressing concerns related to range anxiety and promoting wider EV adoption. We have used ML algorithms such as Polynomial Regression (PR), Random Forest (RF), Linear Regression (LR), and TweedieRegressor (TR) for EV range prediction.

3.3. EV charging location clustering and routing

The mathematical notations used for EV charging clustering and routing are presented in Table 2. Let $D = \{d_1, d_2, \dots, d_m\}$ be a set of m EV charging station data points, where d_i represents a d-dimensional vector in the Euclidean space $\mathbb{R}^d$. The aim is to partition D into k clusters denoted by $C = \{C_1, C_2, \dots, C_k\}$ such that the sum of squared distances from each EV charging station point to its assigned cluster centroid is minimized. We have used K-means clustering in EVerGen. The goal is to minimize $ClusterZone(C, \mu)$ concerning both the cluster assignments C and the cluster centroids μ. The initialization, assignment, and update steps are stated as follows [28]:

- **Initialization**: Randomly select k data points from D as the initial cluster centroids $\mu_1^{(0)}, \mu_2^{(0)}, \dots, \mu_k^{(0)}$.
- **Assignment**: Assign each data point d_i to the cluster with the nearest centroid as follows [28]:

$$C_i = \arg\min_j \|d_i - \mu_j\|^2 \tag{1}$$

- **Update**: Update each cluster centroid to the mean of all data points assigned to that cluster as follows [28]:

$$\mu_j^{(\tau+1)} = \frac{1}{|C_j|} \sum_{d \in C_j} d \tag{2}$$

where τ denotes the iteration number. Repeat the assignment and update steps until convergence, i.e., the cluster assignments no longer change significantly or a maximum number of iterations is reached. Then we find the final set of EV charging station clusters and the corresponding centroids.

EV Routing using MGA: A road network is considered, and there are several charging stations. Let $G = (V, E)$ be a directed graph representing the EV transportation network, where $V = \{v_0, v_1, v_2, \dots, v_l\}$ is the set of vertices. Vertex v_0 represents the depot, and vertices $\{v_1, v_2, \dots, v_l\}$ represent the locations. E is the set of edges between the vertices. Edge e_{ij} represents a directed connection from v_i to v_j.

Our main objective is to minimize the total cost, distance, or travel time, depending on the user's preference. The objective function is given as,

$$\text{Minimize} \quad \sum_{i=0}^{l} \sum_{j=0}^{l} Criterion_{ij_r} \cdot a_{ij_r} \tag{3}$$

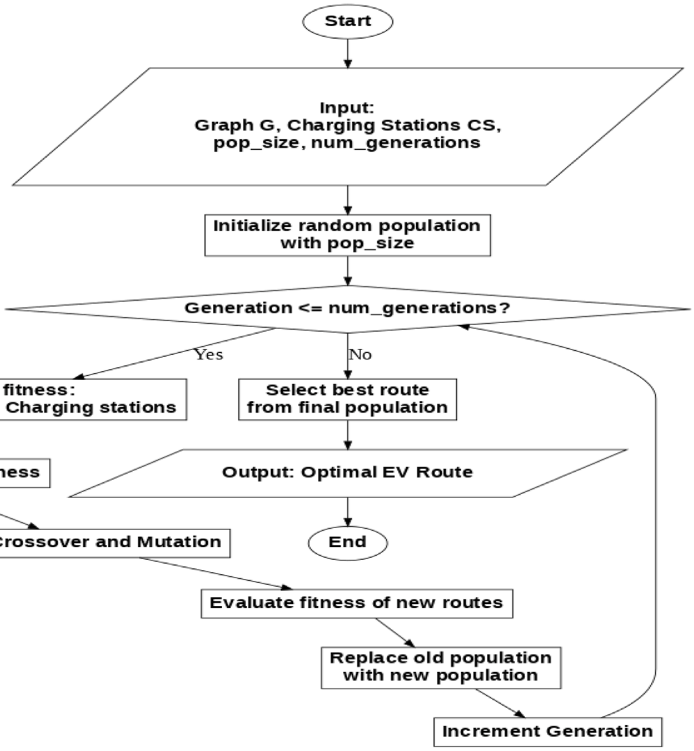

Fig. 2. Flow chart of EV routing using MGA.

subject to:

$$a_{ij_r} \in \{0,1\} \quad \forall v_i, v_j \in V \tag{4}$$

$$\sum_{j=0}^{l} q_j \cdot a_{ij_r} \le Q \quad \forall i \in \{1,2,\dots,l\} \tag{5}$$

$$(\zeta_0 - \sum_{i=0}^{l} q_i \cdot a_{ij_r}) \ge \zeta_{min} \quad \forall j \in \{1,2,\dots,l\} \tag{6}$$

$$\sum_{i=1}^{l} t_{ij_r} \cdot a_{ij_r} \le T_{\max} \quad \forall j \in \{1,2,\dots,l\} \tag{7}$$

where $Criterion_{ij_r} = dist_{ij_r}$, $Criterion_{ij_r} = cost_{ij_r}$, or $Criterion_{ij_r} = time_{ij_r}$, depending on the user's preference, r represents the route between v_i and v_j, and a_{ij_r} represents the binary decision variable. If the user travels from v_i to v_j via route r, then $a_{ij_r} = 1$, otherwise $a_{ij_r} = 0$. The objective function is presented in Eq. (3). Eq. (5) denotes the EV energy constraint. Eq. (6) denotes the energy balance at each location i.e. the difference between the initial energy level and the energy consumption during travel should not be less than the energy threshold (ζ_{min}). Eq. (7) presents that the traveling time should not exceed the maximum allowable traveling time ($T_{\max}$).

To meet the objective function, we propose an MGA-based EV routing strategy in Algorithm 1 and Fig. 2. The MGA is illustrated in Section 3.1. The MGA involves creating an initial random population of routes, evaluating the fitness of each route based on distance, battery usage, and charging stations, selecting routes for reproduction, applying crossover and mutation operators to create new routes, and finally selecting the best route from the final population. The MGA begins with randomly generating an initial population of routes. This population represents a diverse set of potential solutions, with each route serving as an individual in the population. The algorithm starting with a random selection, ensures a broad search space, increasing the chances of finding an optimal or near-optimal solution through subsequent evolutionary steps like selection, crossover, and mutation. This diversity in the initial population is crucial for avoiding premature convergence and exploring a wide range of possibilities during the optimization process.

EV Path Planning: EV path planning is a multifaceted process that requires careful consideration of various parameters to optimize the route, enhance energy efficiency, and ensure a seamless driving experience. Energy consumption is crucial in path

Algorithm 1: EV Routing using MGA

```
Input: Graph ($G$) representing the road network, Charging stations ($CS$), Population size ($pop\_size$), Number of generations
       ($num\_generations$)
Output: Optimal route for EV

Initialize random population with $pop\_size$;
for $gen \leftarrow 1$ to $num\_generations$ do
    Evaluate the fitness of each route based on distance, battery usage, and charging stations;
    Select routes for reproduction based on fitness;
    Apply crossover and mutation operators to create new routes;
    Evaluate fitness of the new routes;
    Replace the old population with the new population;
end
Select the best route from the final population based on fitness;
```

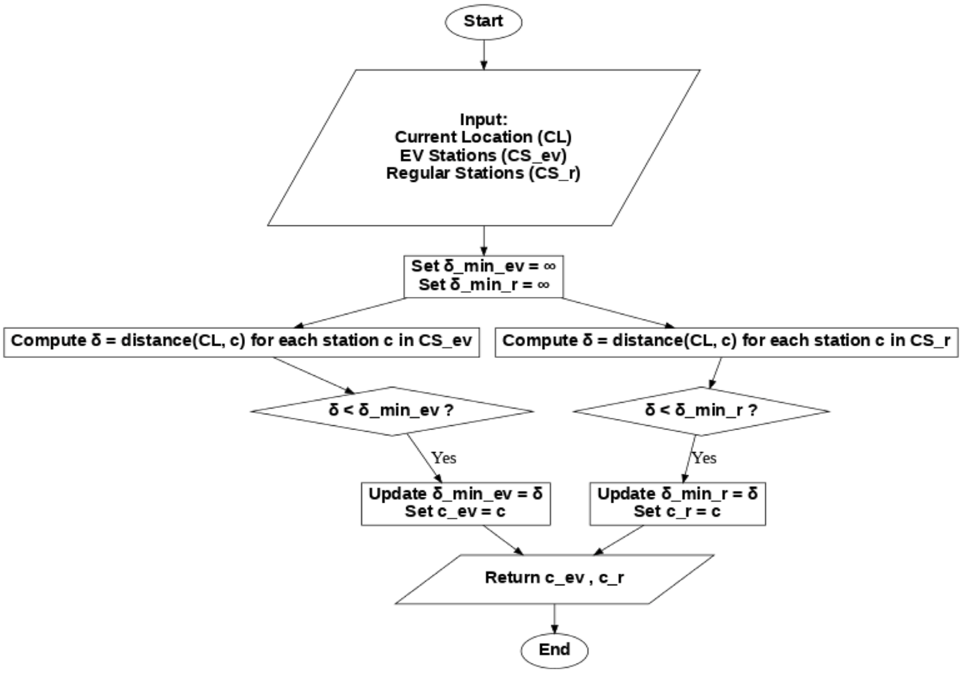

Fig. 3. Flow chart of finding nearest charging stations.

planning, especially for EVs, where battery range is a critical constraint. Road characteristics and speed profiles greatly impact energy consumption of EVs. Route planning by considering these factors helps to minimize energy usage, reduce the need for frequent charging, and extend the battery range for EVs. The current state of charge (SoC) of the EV's battery is also crucial, as the algorithm must ensure that the EV reaches its destination without depleting the battery entirely. Charging infrastructure plays a pivotal role in the planning process. Real-time traffic data is essential for avoiding congestion and dynamically adjusting the path based on traffic conditions, contributing to reduced travel time and optimized energy consumption. Furthermore, road characteristics, including the type of road, and traffic, are integral considerations for a holistic path planning approach. These parameters collectively contribute to an efficient and sustainable EV path planning, addressing energy conservation and overall driving convenience. The process to find the nearest charging station is stated in Algorithm 2 and Fig. 3. In the algorithm, $\delta_{min_{ev}}$ denotes minimum distance to EV charging station, and δ_{min_r} denotes minimum distance to regular charging station.

In Fig. 4, the flow diagram of EV routing is presented, where the minimum battery threshold level for traveling is assumed 30%. The EV range is predicted first. If the battery level is below 30%, the current location is traced and the cluster zone is selected. After that the nearest available charging station is selected and EV charging time is predicted. Based on the predicted charging time, the user selects nearby amenities for refreshment purposes, and after charging is over, the optimal path is found to reach the destination.

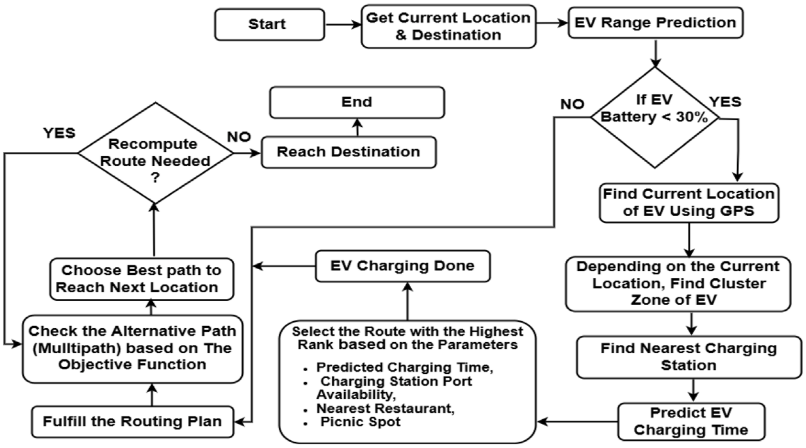

Fig. 4. Flow diagram of EV routing.

Algorithm 2: Find Nearest Charging Stations

```
Input: Current location of the EV ($CL$), List of EV charging stations ($CS_{ev}$), List of regular charging stations ($CS_r$)
Output: Nearest EV charging station ($c_{ev}$), Nearest regular charging station ($c_r$)
$\delta_{min_{ev}} \leftarrow \infty$;
$\delta_{min_r} \leftarrow \infty$;
for each charging station $c$ in $CS_{ev}$ do
    $\delta \leftarrow$ distance between $CL$ and $c$;
    if $\delta < \delta_{min_{ev}}$ then
        $\delta_{min_{ev}} \leftarrow \delta$;
        $c_{ev} \leftarrow c$;
    end
end
for each charging station $c$ in $CS_r$ do
    $\delta \leftarrow$ distance between $CL$ and $c$;
    if $\delta < \delta_{min_r}$ then
        $\delta_{min_r} \leftarrow \delta$;
        $c_r \leftarrow c$;
    end
end
return $c_{ev}$, $c_r$;
```

EV Safety Index: The EV safety index is mathematically defined as:

$$EVSI = \left(\prod_{y=1}^{N_s} \gamma_y^{\omega_y} \right)^{\frac{1}{\sum_{y=1}^{N_s} \omega_y}} \tag{8}$$

γ_y denotes normalized score (between 0 and 1) for the *y*th safety parameters (battery safety, advanced driver-assistance systems, structural integrity, emergency response, cybersecurity, etc.), w_y denotes the weight assigned to the *y*th safety parameter, reflecting its relative importance, and N_s represents the total number of safety parameters. The safety performance is classified into four categories based on the EVSI value: Poor (EVSI: 0–0.5), Moderate (0.5–0.7), Good (0.7–0.9), and Excellent (0.9–1.0).

In the next section, the performance of the proposed strategy EVerGen is analyzed in terms of range prediction accuracy, charging time prediction accuracy, travel time, energy consumption, and safety score.

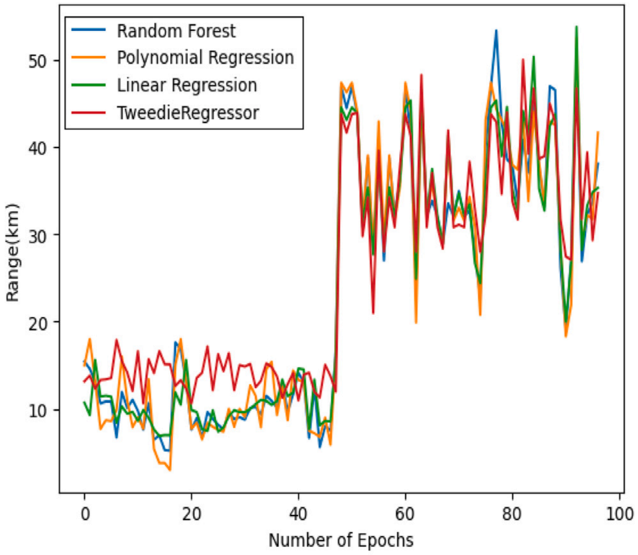

Fig. 5. EV range prediction with charge ≥ 30%.

4. Performance evaluation

The performance of EVerGen is evaluated in terms of EV range prediction accuracy, charging time prediction accuracy, travel time, traveling distance, and energy consumption of the EV during travel time, based on the dataset[1]. The dataset contains information about the EV models, including their performance metrics, specifications, location data, vehicle range, and charging time. The features of the dataset includes Car Model, Rated Power (W), Max Power (W), Top Speed (mph), Battery Capacity (kwh), Charging Time (Hrs), and Range (km). The top speed indicates the maximum speed the EV can reach, and battery capacity denotes the total energy storage capacity of the vehicle's battery. The charging time refers to the time required to charge the battery from empty to complete fully, and the range refers to the maximum distance the EV can travel on a full charge.

4.1. EV range prediction accuracy

In Fig. 5, we compare the performance of PR, RF, LR, and TR, for EV range prediction.

The performance of the ML models is evaluated based on their convergence and stability over multiple training iterations. The performance of each model was tracked over successive epochs, focusing on the key performance metrics accuracy and Root Mean Squared Error (RMSE). From the results it is observed that each model adapts over time and exhibits overfitting or underfitting, and their predictions are stabilized with increased training. We observe from the results that the accuracy in EV range prediction using PR, RF, LR, and TR are 98.36%, 96.75%, 93.8%, and 85.33%, respectively. As we observe, PR has achieved better performance than the other models. The EV charging time is also predicted using Multiple Linear Regression (MLR), Decision Tree (DT), and RF, and presented in Fig. 6. The charging time prediction accuracy for MLR, DT, and RF, are 95.5%, 98.01%, and 96.23%, respectively. We observe that DT has achieved the best performance in charging time prediction.

4.2. Charging location clustering and performance of EV routing model

For location clustering and path planning, we have considered location information, road traffic, and road type, along with the EV range, battery level, and charging station availability. Using K-means clustering, EV charging locations are divided into ten clusters as presented in Fig. 7. Based on the data, ten locations are considered, thus, we set the value of K to 10. Here, we have considered ten following locations: Kolkata (set as Depot), Purulia, Asansol, Durgapur, Bankura, Jamshedpur, Kharagpur, Haldia, Bardhaman, and Kalyani. There are three routes connecting different locations, and the traveler travels among these locations. A real-life scenario is presented in Fig. 8, where the starting location (depot) is set to Kolkata. We observe that after considering all parameters for EV routing, the near-optimal paths are found for the overall scenario.

Based on three criteria: minimum distance, minimum cost, and minimum travel time, three cases are presented in Tables 3, 4, and 5 respectively. The travel cost refers to the transportation cost, which is a function of the distance traveled and the monetary

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[1] https://github.com/SUSHOVANKHATUA/EV_Path_Planning

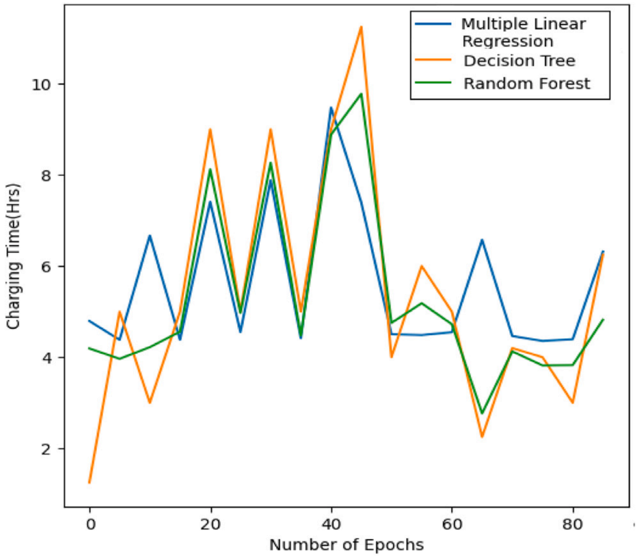

Fig. 6. EV charging time prediction.

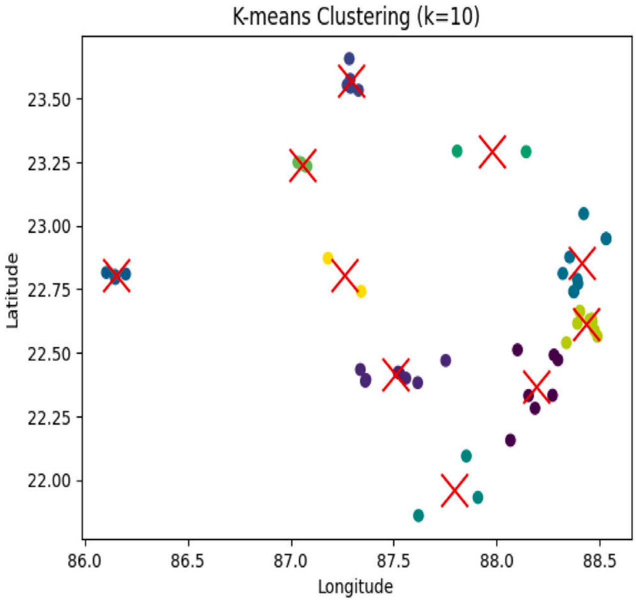

Fig. 7. EV charging location clustering.

cost for charging the EV to travel that distance. As we observe in all three cases, the proposed path planning approach performs better.

Path Selection with Minimal Distance: In a multi-path scenario, the optimal path is chosen based on user preference of distance, cost, or time. If total distance is the preference, the optimal path is 0(1)-3(1)-7(0)-2(2)-1(2)-5(1)-9(0)-4(1)-6(0)-8(1)-0, as presented in Table 3. The reduction in traveling distance using the proposed approach is ∼10%.

Path Selection with Minimal Cost: If total cost is the preference, the optimal path is 0(1)-1(2)-5(2)-8(0)-3(1)-6(1)-9(2)-2(1)-4(2)-7(2)-0, as presented in Table 4. We observe that the reduction in cost using the proposed approach is ∼17%.

Path Selection with Minimal Time: If total time is the preference, the optimal path is 0(1)-9(2)-1(0)-3(1)-4(1)-8(1)-2(2)-5(0)-7(0)-6(1)-0, as presented in Table 5. The reduction in travel time using the proposed approach is ∼14%.

We also observe from Tables 3, 4, and 5 that the energy consumption of the EV during the travel period is lower if the user's preference is minimal distance or minimal time consumption. In both cases, the energy consumption of the EV is 72

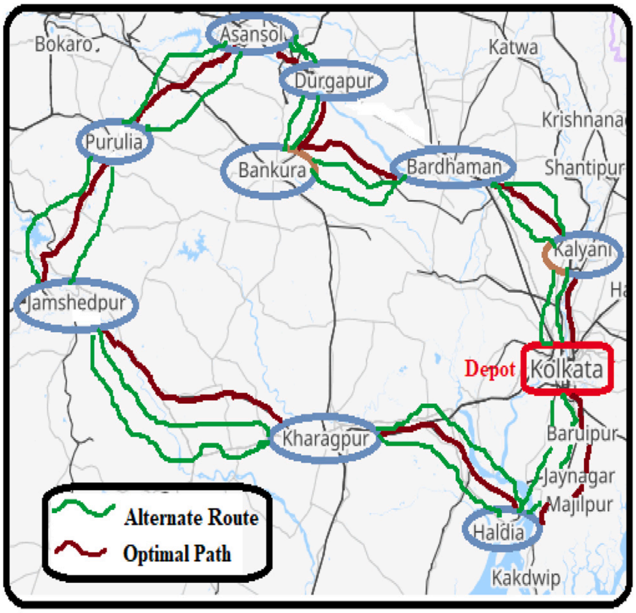

Fig. 8. Optimal routing plan for different regions.

Table 3
Minimize total distance for EV Routing.

	Proposed optimal path planning route	Conventional path path planning route
Routing Path	0(1) -3(1)- 7(0)- 2(2)- 1(2)- 5(1)-9(0)- 4(1)- 6(0)- 8(1)-0	0(0)-8(0)-3(0)-1(0) -5(0)-4(0)-1(0) -2(0)-7(0)-6(0)-0
Travel Time (Hrs)	4.8	5.4
Additional Time including total charging time (Hrs)	2.8	3.7
Total Travel Time (Hrs)	7.6	9.1
Number of EV Charging Used	3	4
Energy consumption of the EV (KWh)	**72**	81
Total Traveling Distance (km)	**356**	398
Travel cost (INR)	1359	1618

Table 4
Minimize total cost for EV Routing.

	Proposed optimal path planning route	Conventional path planning route
Routing Path	0(1) -1(2)- 5(2)- 8(0)- 3(1)- 6(1)-9(2)- 2(1)- 4(2)- 7(2)-0	0(0)-6(0)-7(0)-3(0) -9(0)-4(0)-2(0) -1(0)-5(0)-8(0)-0
Travel Time (Hrs)	4.9	5.3
Additional Time including total charging time (Hrs)	2.5	3.6
Total Travel Time (Hrs)	7.4	8.9
Number of EV Charging Used	3	4
Energy consumption of the EV (KWh)	73.5	79.5
Total Traveling Distance (km)	362	412
Total Travel cost (INR)	**1262**	1519

KWh, which is ~11% lower than the energy consumption of the EV if the conventional single-path approach is followed. If the user's preference is minimal distance and minimal energy consumption, the optimal path is 0(1)-3(1)-7(0)-2(2)-1(2)-5(1)-9(0)-4(1)-6(0)-8(1)-0. If the user's preference is minimal travel time and minimal energy consumption, the optimal path is 0(1)-9(2)-1(0)-3(1)-4(1)-8(1)-2(2)-5(0)-7(0)-6(1)-0.

Table 5
Minimize total time for EV Routing.

	Proposed optimal path planning route	Conventional path planning route
Routing Path	0(1) -9(2)- 1(0)- 3(1)- 4(1)- 8(1)-2(2)- 5(0)- 7(0)- 6(1)-0	0(0)-7(0)-3(0)-5(0) -4(0)-1(0)-6(0) -2(0)-9(0)-8(0)-0
Travel Time (Hrs)	4.8	5.4
Additional Time including total charging time (Hrs)	2.5	3.1
Total Travel Time (Hrs)	**7.3**	8.5
Number of EV Charging Used	3	4
Energy consumption of the EV (KWh)	**72**	81
Total Traveling Distance (km)	359	407
Travel cost (INR)	1354	1598

Table 6
Benchmark comparison of MGA with classical GA, PSO, and ACO.

Instance	BKS	MGA			GA			PSO			ACO		
		BFS	Iter	Time (s)	BFS	Iter	Time (s)	BFS	Iter	Time (s)	BFS	Iter	Time (s)
gr17	2085	2085	80	0.10	2085	89	0.16	2087	95	0.21	2086	92	0.25
gr21	2707	2707	185	0.13	2710	187	0.22	2715	210	0.31	2712	205	0.36
gr24	1272	1272	190	0.15	1273	225	1.23	1276	240	1.42	1274	235	1.58
gr120	6942	6943	920	4.65	6945	1430	6.98	6980	1580	7.81	6965	1510	8.22
a280	2579	2579	1621	8.56	2885	1970	11.97	2635	2100	13.25	2612	2050	14.81
kroB200	29,437	29,456	1420	6.81	30,124	1820	9.86	29,890	1950	10.92	29,775	1880	11.34
kroB200	29,437	29,441	1450	6.91	30,129	1819	9.87	29,875	1940	10.85	29,760	1895	11.52
a280	2579	2581	1620	8.32	2847	1970	12.25	2642	2095	13.41	2625	2062	14.66
pr1002	259,045	299,491	2550	15.48	369,546	2743	23.58	315,820	2980	26.14	309,775	2870	28.92
pcb3038	137,694	169,135	2983	23.39	187,561	2980	27.21	176,420	3105	31.44	171,880	3050	33.12

BKS: best-known solution, BFS: best-found solution, Iter: iterations

Table 7
Performance comparison of single-path and multi-path routing using EV safety index.

Method	Single Path Node(0, S_{Val})	Multi Path Node(Route, S_{Val})	T_{SPS}	T_{MPS}
PSO	0(0,0.6)-6(0,0.8)-7(0,0.9)-2(0,0.5)-9(0,0.7)-1(0,0.6)-4(0,0.8)-3(0,0.5)-5(0,0.7)-8(0,0.6)	0(1,0.8)-5(2,0.7)-9(0,0.8)-7(1,0.6)-3(2,0.7)-8(1,0.8)-2(0,0.9)-6(2,0.8)-4(1,0.7)-1(0,0.7)	6.7	7.5
ACO	0(0,0.7)-2(0,0.6)-5(0,0.8)-8(0,0.9)-1(0,0.7)-7(0,0.6)-3(0,0.8)-9(0,0.5)-4(0,0.7)-6(0,0.6)	0(0,0.8)-3(1,0.8)-7(2,0.7)-9(1,0.6)-2(0,0.8)-8(2,0.9)-1(1,0.7)-6(0,0.7)-4(2,0.8)-5(1,0.7)	6.9	7.8
GA	0(0,0.9)-5(0,0.8)-8(0,0.9)-2(0,0.7)-6(0,0.8)-9(0,0.9)-4(0,0.7)-7(0,0.8)-3(0,0.9)-1(0,0.8)	0(2,0.9)-6(1,0.9)-1(0,0.8)-3(2,0.8)-8(1,0.9)-2(0,0.8)-5(2,0.8)-9(1,0.8)-4(0,0.8)-7(2,0.7)	8.2	8.4
Proposed MGA	0(0,0.9)-6(0,0.7)-9(0,0.8)-3(0,0.9)-7(0,0.9)-1(0,0.8)-4(0,0.9)-8(0,0.9)-2(0,0.8)-5(0,0.8)	0(1,0.9)-7(2,0.9)-2(0,0.8)-4(1,1)-9(2,0.9)-3(0,0.8)-6(1,0.9)-1(2,1)-5(0,0.8)-8(1,0.9)	**8.4**	**8.9**

S_{Val}: Safety value, T_{SPS}: Total Single path Safety, T_{MPS}: Total Multi path Safety.

4.2.1. Computational complexity analysis

Let N denotes the total number of nodes, k denotes the number of clusters, P denotes the population size, $\mathcal{G}$ denotes the number of generations, and E denotes the number of edges in the road network. During clustering, each node is assigned to the nearest centroid among k clusters. The computational cost per iteration is $O(N \cdot k)$. If the clustering stabilizes after I iterations, the total clustering complexity becomes $O(I \cdot N \cdot K)$. In the routing stage, each chromosome (route) is evaluated using distance, cost, time, and EV safety index across the network graph. The fitness evaluation requires $O(P \cdot E)$ per generation. Over $\mathcal{G}$ generations, the routing complexity becomes $O(\mathcal{G} \cdot P \cdot E)$. Thus, the total computational complexity of the proposed framework is $O(I \cdot N \cdot k + \mathcal{G} \cdot P \cdot E)$.

4.3. Comparison with classical ga, aco, and PSO

The benchmark results of MGA compared to classical GA, ACO, and PSO are presented in Table 6. The best-known solution (BKS) and best-found solution (BFS) are presented. We observe that the proposed MGA achieves better performance than the classical GA, ACO, and PSO. To verify large-scale performance of the proposed approach, we have tested it on benchmark instances up to 3038 nodes obtained from the TSPLIB dataset.[2] The corresponding results presented in Table 6 confirm that the proposed method efficiently handles large-scale real-world optimization problems.

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[2] https://www.math.uwaterloo.ca/tsp/world/index.html

Table 8
Performance comparison of single-path and multi-path approaches based on safety metrics (40 nodes).

Objective	Single Path (Node(0, S_{Val}))	Multi Path (Node(Route, S_{Val}))	T_{SPS}	T_{MPS}
Distance	0(0,0.6)-1(0,0.7)-2(0,0.8)-3(0,0.6)-4(0,0.7)-5(0,0.8)-6(0,0.7)-7(0,0.6)-8(0,0.8)-9(0,0.7)-10(0,0.6)-11(0,0.7)-12(0,0.8)-13(0,0.6)-14(0,0.7)-15(0,0.8)-16(0,0.7)-17(0,0.6)-18(0,0.8)-19(0,0.7)-20(0,0.6)-21(0,0.7)-22(0,0.8)-23(0,0.6)-24(0,0.7)-25(0,0.8)-26(0,0.7)-27(0,0.6)-28(0,0.8)-29(0,0.7)-30(0,0.6)-31(0,0.7)-32(0,0.8)-33(0,0.6)-34(0,0.7)-35(0,0.8)-36(0,0.7)-37(0,0.6)-38(0,0.8)-39(0,0.7)	0(1,0.8)-1(2,0.7)-2(0,0.8)-3(1,0.7)-4(2,0.8)-5(0,0.7)-6(1,0.8)-7(2,0.7)-8(0,0.9)-9(1,0.8)-10(2,0.7)-11(0,0.8)-12(1,0.9)-13(2,0.8)-14(0,0.7)-15(1,0.8)-16(2,0.9)-17(0,0.8)-18(1,0.9)-19(2,0.8)-20(0,0.7)-21(1,0.8)-22(2,0.9)-23(0,0.8)-24(1,0.9)-25(2,0.8)-26(0,0.7)-27(1,0.8)-28(2,0.9)-29(0,0.8)-30(1,0.9)-31(2,0.8)-32(0,0.7)-33(1,0.8)-34(2,0.9)-35(0,0.8)-36(1,0.9)-37(2,0.8)-38(0,0.9)-39(1,0.8)	28.0	33.2
Cost	0(0,0.8)-1(0,0.9)-2(0,0.8)-3(0,0.9)-4(0,0.8)-5(0,0.9)-6(0,0.8)-7(0,0.9)-8(0,0.8)-9(0,0.9)-10(0,0.8)-11(0,0.9)-12(0,0.8)-13(0,0.9)-14(0,0.8)-15(0,0.9)-16(0,0.8)-17(0,0.9)-18(0,0.8)-19(0,0.9)-20(0,0.8)-21(0,0.9)-22(0,0.8)-23(0,0.9)-24(0,0.8)-25(0,0.9)-26(0,0.8)-27(0,0.9)-28(0,0.8)-29(0,0.9)-30(0,0.8)-31(0,0.9)-32(0,0.8)-33(0,0.9)-34(0,0.8)-35(0,0.9)-36(0,0.8)-37(0,0.9)-38(0,0.8)-39(0,0.9)	0(2,0.9)-1(1,0.8)-2(0,0.9)-3(2,0.9)-4(1,0.8)-5(0,0.9)-6(2,0.9)-7(1,0.8)-8(0,0.9)-9(2,0.9)-10(1,0.8)-11(0,0.9)-12(2,0.9)-13(1,0.8)-14(0,0.9)-15(2,0.9)-16(1,0.8)-17(0,0.9)-18(2,0.9)-19(1,0.8)-20(0,0.9)-21(2,0.9)-22(1,0.8)-23(0,0.9)-24(2,0.9)-25(1,0.8)-26(0,0.9)-27(2,0.9)-28(1,0.8)-29(0,0.9)-30(2,0.9)-31(1,0.8)-32(0,0.9)-33(2,0.9)-34(1,0.8)-35(0,0.9)-36(2,0.9)-37(1,0.8)-38(0,0.9)-39(2,0.9)	34.0	36.8
Time	0(0,0.9)-1(0,0.9)-2(0,0.8)-3(0,0.9)-4(0,0.9)-5(0,0.8)-6(0,0.9)-7(0,0.9)-8(0,0.8)-9(0,0.9)-10(0,0.9)-11(0,0.8)-12(0,0.9)-13(0,0.9)-14(0,0.8)-15(0,0.9)-16(0,0.9)-17(0,0.8)-18(0,0.9)-19(0,0.9)-20(0,0.8)-21(0,0.9)-22(0,0.9)-23(0,0.8)-24(0,0.9)-25(0,0.9)-26(0,0.8)-27(0,0.9)-28(0,0.9)-29(0,0.8)-30(0,0.9)-31(0,0.9)-32(0,0.8)-33(0,0.9)-34(0,0.9)-35(0,0.8)-36(0,0.9)-37(0,0.9)-38(0,0.8)-39(0,0.9)	0(1,0.9)-1(2,0.9)-2(0,0.8)-3(1,0.9)-4(2,0.9)-5(0,0.8)-6(1,0.9)-7(2,0.9)-8(0,0.8)-9(1,0.9)-10(2,0.9)-11(0,0.8)-12(1,0.9)-13(2,0.9)-14(0,0.8)-15(1,0.9)-16(2,0.9)-17(0,0.8)-18(1,0.9)-19(2,0.9)-20(0,0.8)-21(1,0.9)-22(2,0.9)-23(0,0.8)-24(1,0.9)-25(2,0.9)-26(0,0.8)-27(1,0.9)-28(2,0.9)-29(0,0.8)-30(1,0.9)-31(2,0.9)-32(0,0.8)-33(1,0.9)-34(2,0.9)-35(0,0.8)-36(1,0.9)-37(2,0.9)-38(0,0.8)-39(1,0.9)	34.8	37.6

S_{Val}: Safety value, T_{SPS}: Total Single path Safety, T_{MPS}: Total Multi path Safety.

Table 7 presents a comparative evaluation of different optimization techniques using the proposed EV Safety Index-based routing framework under both single-path and multi-path strategies. The results show that the multi-path routing consistently achieves higher safety than the single-path routing for all cases. This improvement occurs because multi-path exploration provides alternative safer routes, reduces exposure to risky nodes, and balances route-level uncertainty. The obtained results demonstrate that multi-path routing consistently achieves higher EV Safety Index values than single-path routing for all evaluated cases, indicating improved travel safety through the use of alternative routes. We have also drawn a comparison among the safety scores obtained using MGA, PSO, ACO, and classical GA. PSO attains safety scores of 6.7 (single-path) and 7.5 (multi-path), while ACO slightly improves the performance to 6.9 and 7.8, respectively. The classical GA shows better performance with safety indices of 8.2 (single-path) and 8.4 (multi-path). Notably, the proposed MGA achieves the overall best performance, reaching the highest EV Safety Index values of 8.4 for single-path and 8.9 for multi-path routing, thereby demonstrating superior route safety and effectiveness compared to PSO, ACO, and classical GA. PSO and ACO demonstrate gradual safety improvement in multi-path mode, indicating that their stochastic search capabilities can partially capture safer routes. Classical GA performs strongly ($T_{SPS} = 8.2$, $T_{MPS} = 8.4$) due to population-based exploration and exploitation balance. The proposed MGA achieves the overall best performance, with $T_{SPS} = 8.4$ and $T_{MPS} = 8.9$, demonstrating superior safety optimization. Furthermore, to demonstrate the practical applicability of the proposed approach, the performance is analyzed considering a 40-node real-life EV scenario, and the results are presented in Table 8. Here, the safety score is determined for the single-path and multi-path scenarios based on the objective of minimum distance or minimum cost or minimum travel time for optimal path planning.

4.4. Comparison with existing frameworks

The proposed approach EVerGen is compared with the existing frameworks on EVs in Table 9. In [7], XGBR and LGBR were used for EV range prediction, and an RMSE of 0.75 was achieved. In [13], adaptive two step filter was used and an RMSE of 1.8105 was achieved in velocity prediction, and a prediction error of 0.859 in case of battery state of available power. In [18], LR was used for charging time prediction, and 92% accuracy was achieved. The proposed framework EVerGen has achieved above 98% accuracy in EV range prediction and charging time prediction. We also observe that the computation time in EVerGen is lower compared to the existing approaches [7,13,18]. Thus, we conclude that EVerGen performs better than the existing frameworks.

Table 9
Comparison of the proposed and existing approaches.

Work	Classifier	Prediction accuracy (range/ battery power/ velocity)	Computation time (seconds)
Zhao, L. et al. [7]	XGBR, LGBR	RMSE: 0.75 (range prediction)	79
Yang, L. et al. [13]	Adaptive Two Step Filter	RMSE: 1.8105 (velocity prediction), prediction error: 0.859 (battery state of available power)	86
Bi, Jun, et al. [18]	Regression	92% (charging time)	83
Proposed work (EVerGen)	PR (highest), RF, LR, TR (range prediction), DT (highest), MLR, RF (charging time prediction)	98.36%, RMSE: 0.5 (range prediction), 98.01% (charging time)	61

5. Conclusions and future work

The need for sustainable transportation solutions in an eco-friendly environment has increased the popularity of EVs. However, the range prediction is significant to estimate the distance an EV can travel for recharging. This paper has proposed an EV range prediction strategy using ML, and the proposed approach has achieved >98% prediction accuracy. When the battery level is low, it is also important to find a nearby available charging point. Using K-means clustering the present zone of the EV is selected and the nearby charging point is traced. The charging time is also predicted using ML so that the user can search nearby amenities for refreshments. The results show that the proposed approach has achieved >98% accuracy in charging time prediction. Finally, to reach the destination at a minimal distance, minimal time, or minimal cost, an optimal path planning strategy has been proposed using MGA. The results present that the MGA outperforms the PSO, ACO, and classical GA. The proposed path planning strategy accesses road traffic information, road type, charging station availability, location, and battery level, allowing for more informed and dynamic route optimization. The proposed EV routing strategy outperforms the conventional path planning approach in terms of distance, time, cost, and energy consumption by ∼10%, ∼14%, ∼17%, and ∼11%, respectively.

In EVerGen, the vehicles are used as edge devices, and the data analysis is performed inside the edge devices to reduce the data traffic compared to the cloud-only scenario, where entire data transmission and analysis happen inside the cloud. However, the local dataset of a device may not have sufficient number of samples of each class, and the generated model may not have high prediction accuracy. Generative AI can be used to address the data scarcity and class imbalance issues. However, the analysis of the data collected from various devices may provide an accurate model generation, though the data storage and analysis inside the cloud increase data traffic and compromise data privacy. To address the issue, federated learning can be used to build an accurate model through privacy-aware collaborative training. The use of generative AI and federated learning in IoVT are future research directions of this work. In the future, road surface conditions, weather conditions, mass, resistance factors, will be considered along with location information, road traffic, road type, EV range, battery level, and charging station availability, to improve the routing and prediction model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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