PATH PLANNING CONSIDERING DRIVER PREFERENCES USING ANALYTIC HIERARCHY PROCESS FOR ELECTRIC VEHICLES

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Keywords

Electric vehicle
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Abstract

Sustainable transportation and green logistics are becoming increasingly important, and the efficient use of electric vehicles (EVs) plays a critical role. However, efficient path planning for EVs remains a major challenge due to limited driving range and the need for optimised charging strategies. Usually, path recommendations are made based on a single criterion. However, drivers may want to consider multiple criteria for path selection. This study focuses on building a multi-criteria path planning algorithm that incorporates driver preferences by considering total travel time, energy consumption and travelling distance. To obtain the appropriate recommendation, these three criteria are evaluated using the Analytic Hierarchy Process (AHP) and Dijkstra algorithm is used to identify roads that take into account driver preferences. Johnson technique was used to remove negative energy weights due to energy recovery and solved the incompatibility problem of the Dijkstra algorithm with negative edge weights. The results have shown the proposed algorithm can efficiently generate solutions designed based on driver preferences and is suitable for EV routing applications. This study presents a method to increase user satisfaction by aiming at the widespread adoption of EVs and emphasizes the importance of multi-criteria decision making in addressing the unique challenges of EVs.

ELEKTRİKLİ ARAÇLAR İÇİN ANALİTİK HİYERARŞİ SÜRECİ KULLANARAK SÜRÜCÜ TERCİHLERİNİ DİKKATE ALAN YOL PLANLAMA

Anahtar Kelimeler

Elektrikli araç
Yol planlama
Sürücü tercihi
Analitik Hiyerarşi Süreci
Dijkstra algoritması

Öz

Sürdürülebilir taşımacılık ve yeşil lojistik giderek daha önemli hale gelmektedir ve elektrikli araçların verimli kullanımı kritik bir rol oynamaktadır. Ancak, sınırlı sürüş menzili ve optimize edilmiş şarj stratejilerine duyulan ihtiyaç nedeniyle elektrikli araçlar için verimli yol planlaması büyük bir zorluk olmaya devam etmektedir. Genellikle, yol önerileri tek bir kritere dayalı olarak yapılır. Ancak, sürücüler yol seçimi için birden fazla kriteri göz önünde bulundurmak isteyebilir. Bu çalışma, toplam seyahat süresi, enerji tüketimi ve seyahat mesafesini dikkate alarak sürücü tercihlerini içeren çok kriterli bir yol planlama algoritması oluşturmaya odaklanmaktadır. Uygun öneriyi elde etmek için bu üç kriter Analitik Hiyerarşi Süreci kullanılarak değerlendirilmiş ve sürücü tercihlerini dikkate alan yolları belirlemek için Dijkstra algoritması kullanılmıştır. Enerji geri kazanımı nedeniyle negatif enerji ağırlıklarını kaldırmak için Johnson tekniği kullanılmış ve Dijkstra algoritmasının negatif edge ağırlıkları ile uyumsuzluk sorunu çözülmüştür. Sonuçlar, önerilen algoritmanın sürücü tercihlerine göre tasarlanmış çözümleri verimli bir şekilde üretebildiğini ve elektrikli araç rotalama uygulamaları için uygun olduğunu göstermiştir. Bu çalışma, elektrikli araçların yaygın olarak benimsenmesini hedefleyerek kullanıcı memnuniyetini artırmaya yönelik bir yöntem sunmakta ve elektrikli araçların kendine özgü zorluklarının ele alınmasında çok kriterli karar vermenin önemini vurgulamaktadır.

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1. Introduction

Electric vehicles (EVs) are becoming increasingly popular as global environmental policies encourage a shift away from fossil-fuelled vehicles. EVs have lower fuel consumption, reducing environmental impact and providing higher efficiency than internal combustion engine vehicles (ICEVs) (Ramachandaramurthy et al., 2023). The comparisons made between EVs and ICEVs highlight the advantages of EVs when it comes to total cost of ownership, energy efficiency, emissions, maintenance frequency and acceleration, supporting their growing market potential (Liu et al., 2021). Moreover, numerous governments globally have enacted policies aiming to phase out sales of new ICEVs in a short period of time (Fulton et al., 2019). This shift in the market brings with it new challenges that need to be overcome and optimised in order to increase user demand for EVs compared to ICEVs. EVs can have limited driving range, which causes range anxiety for potential customers, so efficient path planning emerges as an important need (Faraj and Basir, 2016).

EV path planning addresses unique constraints such as limited driving range and low-density charging station network (Eisner, Funke and Storandt, 2011). While route planning of conventional ICEVs includes criteria such as distance, time, travel impediments, scenery and vehicle cost (Pahlavani and Delavar, 2014), EV route planning prioritises energy consumption and charging cost in addition to time and distance (Kucukoglu, Dewil and Cattrysse, 2021). Since a single criterion may not be ideal in urban road networks, the use of personal and commercial EVs may require different routing criteria in terms of satisfaction and efficiency. Multi-criteria decision making (MCDM) based approaches can solve these complex routing problems (Bouakouk, Abdeli, Mokdal and Othman, 2022). MCDM is a helpful procedure for decision making when more than one criterion is available (Gavade, 2014). While MCDM considers limitations such as vehicle capacity and delivery time windows in ICEV applications, it considers criteria such as travel costs, fuel consumption and time efficiency. EVs have specific constraints for MCDM to handle, battery range, location of charging stations, and charging time are a few of them (Abidin, Abidin and Daud, 2025).

There are some studies that include single criteria path planning for EVs (Alizadeh et al., 2014; Artmeier et al., 2010). Most path-planning studies in the literature focus on a single criterion and do not consider driver preferences. Less commonly, some MCDM-based studies exist for EV path planning algorithms. For example, Schoenberg and Dressler (2022) proposed a MCDM-based EV path planning method to reduce waiting times at charging stations. To the best of our knowledge, the application of MCDM in EV path planning has received significantly less attention in the literature compared to single criteria approaches. The contributions of this study can be summarized as follows:

- A path planning algorithm for EVs is proposed by incorporating driver preferences.
- This study focuses on shortest path planning by considering energy consumption, travel time, and distance, while incorporating driver preferences through the Analytical Hierarchy Process (AHP)
- The Dijkstra algorithm is used to calculate the paths based on driver preferences.
- The Johnson technique is employed to handle negative weights in EV-specific energy consumption calculations.

In this study, the aim is to provide path recommendations for EV users in urban travel from a multi-criteria perspective. The study focuses on determining the most suitable path by considering energy consumption, travel time, and travel distance. Additionally, the AHP was employed to incorporate driver preferences into the decision-making process. The novelty of this study lies in weighting the three commonly used objective functions in the literature according to driver preferences through AHP and proposing a single path that simultaneously considers these three criteria based on the derived weights. Thus, the proposed method distinguishes itself from existing studies by offering a personalized path recommendation for EV drivers.

The structure of this paper is as follows: Section 2 reviews the methodology in the context of related literature. Materials and methods are provided in Section 3. Section 4 presents the results, and finally, Section 5 concludes with a discussion, a summary of findings, and future work.

2. Literature Review

There have been several studies in the literature on path planning for EVs. Alizadeh et al. (2014) proposed an EV path planning model that integrates dynamic traffic conditions, electricity costs and charging decisions using an extended transport graph model. Their findings show that coordinated strategies are more effective in minimizing costs and maintaining grid stability. Ding et al. (2020) presented a charging alert and path planning approach that combines traffic information, charging station queues, and energy consumption monitoring in real time.

Researchers have also focused on developing criteria-based routing strategies for electric EVs in addition to classical path planning approaches. Udhan et al. (2022) proposed a modified Dijkstra algorithm in which travel time is prioritised based on physical distance and edges are identified based on traffic density, segment length and average vehicle speed, thus reducing travel time.

Knez, Dumancic, Erdelic and Mardesic (2023) addressed the Energy Shortest Path Problem (ESPP) and Time Dependent Shortest Path Problem (TDSPP) using a modified Dijkstra algorithm. In their study, they showed that energy-optimal paths cause an increase in travel time due to the selection of low-speed urban roads in addition to low-energy paths provided by energy-optimal paths.

Drivers may prefer paths based on more than one objective through MCDM methods. Bozkurt, Yazici and Keskin (2012) presented a multi-criteria route planning approach that integrates driver preferences and combines criteria such as travel time and road safety with a regular pairwise comparison method and regular increasing monotone quantifier guided ordered weighted averaging (OWA) operators. Rosita, Rosyida and Rudiyanto (2019) proposed a system that combines Dijkstra's algorithm with MCDM to improve path selection based on various parameters. With a modification of Dijkstra's algorithm, the shortest paths are generated using normalised weights of criteria such as distance, cost, congestion and risk. The combination of MCDM and Dijkstra's algorithm allowed priorities to be set and path selection to be customised, minimising costs while avoiding high-risk routes. Similarly, Kien Hua and Abdullah (2018) proposed the Weighted Sum Dijkstra Algorithm (WSDA) to address multiple criteria such as cost, distance and time. WSDA was found to outperform the traditional Dijkstra algorithm.

AHP can be applied to manage multiple objectives. Yang and Li (2010) proposed an emergency response routing algorithm for fire rescue operations by integrating Dijkstra's algorithm and AHP in a Geographic Information System (GIS) framework. AHP was used to assign weights to various criteria such as road width, type, traffic and intersection delays. It was observed that this hybrid approach achieved better performance in emergency scenarios compared to the traditional Dijkstra algorithm. In the same direction, Ahmed, Ibrahim and Henfy (2018) proposed an emergency routing method that can integrate eight different criteria by combining AHP method and Dijkstra algorithm. Keser, Yazici and Gunal (2016) integrated the A* algorithm with AHP using criteria such as travel distance, travel time, road safety and fuel consumption. To improve the decision mechanism, Xinlei, Wen, Zhan and Tao (2022) proposed a Fuzzy Analytic Hierarchy Process (FAHP) method integrated with a dynamic Dijkstra algorithm that takes into account driver preferences and real-time traffic fluctuations. Nasution, Husni, Kuspriyanto and Yusuf (2022) applied the Fuzzy Analytic Hierarchy Process–Express (F-AHP-Express) method together with the Dijkstra shortest path algorithm to evaluate multiple route criteria. Ribeiro and Longaray (2024) combined AHP and ELECTRE II for emergency team prioritization, integrated with Dijkstra’s algorithm to determine the shortest response routes on urban road networks. A summary of the literature on path planning algorithms that consider driver preferences is presented in Table 1.

Table 1. Summary of Research on Driver Preferences in Path Planning Algorithms

Study	Evaluated Criteria	MCDM Method	Algorithm
Xinlei et al. (2022)	Cost, passenger flow, construction cost, environmental impact	Fuzzy AHP	Dijkstra
Yang and Li (2010)	Travel time, traffic volume, road type, road width, number of junctions	AHP	Dijkstra
Bozkurt et al. (2012)	Travel time, road safety	Pairwise Comparison and OWA Operators	Dijkstra
Rosita et al. (2019)	Cost, distance, congestion, risk	Custom priority-based weighting	Dijkstra
Ahmed et al. (2018)	Travel time, road type, road length, traffic volume, road width, mass [illegible]	AHP	Dijkstra
Keser et al. (2016)	Travel time, travel distance, road safety, fuel consumption	AHP	A*
Kien Hua and Abdullah (2018)	Distance, safety, comfort, aesthetic view	Weighted Sum Method	Dijkstra
Study	Evaluated Criteria	MCDM Method	Algorithm
Schoenberg and Dressler (2022)	Driving time, waiting time, charging time, energy consumption	Multi-criterion shortest path	A*
Ribeiro and Longaray (2024)	Equipment availability, vehicle type, accessories, operational readiness	AHP and ELECTRE II	Dijkstra
Nasution et al. (2022)	Route length, traffic congestion, travel time, weather, road heterogeneity	Fuzzy AHP	Dijsktra

The literature review reveals that multi-criteria routing studies are common for ICEVs. However, to the best of our knowledge, no existing study in the literature has proposed a path planning algorithm for EVs that explicitly integrates multiple criteria while considering driver preferences.

3. Materials and Methods

In this study, a path planning algorithm is proposed for EVs, integrating the weighting of three different objective functions—total travel distance, total travel time, and total energy consumption—while incorporating driver preferences. The AHP, a multi-criteria decision-making approach, is employed to determine the relative weights of these objectives. Then, Dijkstra algorithm is applied in the routing phase to determine the shortest path.

The proposed multi-criteria path planning algorithm contains two sequential phases. The first phase focuses on generating three different paths, each individually selected based on one of the three criteria (total travel distance, total travel time, and total energy consumption). In the hybrid approach, three criteria are considered during the second phase to propose a route aligned with driver preferences. In this phase, AHP makes it possible to combine these criteria based on the weights assigned by the driver. The effectiveness of the proposed algorithm is evaluated on a graph representation of the Eskişehir Osmangazi University campus environment. The OpenStreetMap (OSM) data is utilized to construct the road network graph. The list of symbols used in the following subsections is provided in Table 2, along with their explanations.

Table 2. Nomenclature

Notation	Description
G	A graph
V	The set of nodes in a graph
E	The set of edges in a graph
W	Edge weight
v_k	A node $v_k \in V$
t_{ij}	Travel time on the edge (*i, j*)
e_{ij}	Energy consumption on the edge (*i, j*)
d_{ij}	distance of edge (*i, j*)
sl_{ij}	Average speed on the edge (*i, j*)
E_{pot}	Potential energy
E_{kin}	Kinetic energy
E_{rot}	Rotational energy
E_{gain}	Energy gain
E_{veh}	Energy of the vehicle
E_{loss}	Energy loss
E_{air}	Aerodynamic drag energy
E_{roll}	Rolling resistance energy
E_{const}	Constant power consumption energy
P_{const}	Constant power consumption
E_{bat}	Energy contained in the battery
η_{prop}	Propulsion efficiency
η_{recup}	Recuperation efficiency
m	Mass of the vehicle
g	Gravitational acceleration
h	Elevation
v	Current velocity of the vehicle
J	Rotational inertia/moment of inertia
ρ	Air density
C_d	Drag coefficient
A	Frontal area of the vehicle
C_{roll}	Rolling resistance coefficient
Δs	Covered distance
Δt	Time interval
x_i	Original value of the given criterion
x_{max}	The maximum score of the criterion
λ_{max}	Largest eigenvalue of a matrix
x_{ij}^l	Criterion value for that edge
u_l	Weight of that criterion

3.1. Objective Functions in Path Optimization

The road network representing the testing area was constructed using the OSMnx library from an .osm file containing map data in XML format. For simplification and prevention of node connection issues, the graph was filtered to retain drivable road types only. The directed graph of a road network can be represented as $G(V,E)$ which defined as an ordered pair of nodes V and edges E. Here, each node $v_k \in V$ represented by its latitude, longitude and altitude information, where $v_k \in V(k = 1,2,3,\dots,n)$ and $(v_i, v_j) \in E$, $i,j = 1,2,3,\dots,n, i \neq j$. For each pair of v_i and v_j are neighbor nodes which represent an edge that is associated with a weight based on defined criteria. Elevation data from a GeoTIFF file was added to nodes to enable slope calculations used in energy modeling. Each edge in the road network was attached to weights for travel time (t_{ij}), travel distance (d_{ij}) and energy consumption (e_{ij}).

Travel time

The travel time value for each edge was calculated using the road length and the average speed of the traveled highway types (e.g., 110 km/h for motorways, 50 km/h for primary roads). The travel time that results in minutes is calculated using Equation 1, where sl_{ij} is the average speed on the edge.

$$t_{ij} = d_{ij} \; / \; sl_{ij} \tag{1}$$

Travel distance

The travel distance represents a straightforward metric of travel distance based on the physical length of the road segment in kilometers obtained from the .osm file.

Energy consumption

The energy consumption for each road segment is determined by considering the physical energy required to travel that segment. These demands consider constant power consumption, resistive forces, elevation changes, and velocity variations. It is computed for discrete time step k using detailed energy models (Kurczveil, López, and Schnieder 2014). The vehicle's energy obtained by the kinetic energy, the potential and the rotational energy in Equation 2, energy gain between time steps k and $k+1$ in Equation 3, energy loss in Equation 4, air resistance in Equation 5, rolling resistance in Equation 6, and constant power intake in Equation 7. Then, the energy contained in the vehicle's battery depending on propulsion and recuperation in Equation 8 and Equation 9.

$$E_{veh}[k] = E_{kin}[k] + E_{pot}[k] + E_{rot}[k] = m \cdot g \cdot h[k] + \frac{m}{2} \cdot v^2[k] + \frac{J}{2} \cdot v^2[k] \quad (2)$$

$$\Delta E_{gain}[k] = E_{veh}[k+1] - E_{veh}[k] - \Delta E_{loss}[k] \quad (3)$$

$$\Delta E_{loss}[k] = \Delta E_{air}[k] + \Delta E_{roll}[k] + \Delta E_{const}[k] \quad (4)$$

$$\Delta E_{air}[k] = \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot v^2[k] \cdot |\Delta s[k]| \quad (5)$$

$$\Delta E_{roll}[k] = C_{roll} \cdot m \cdot g \cdot |\Delta s[k]| \quad (6)$$

$$\Delta E_{const}[k] = P_{const} \cdot \Delta t \quad (7)$$

$$E_{bat}[k+1] = E_{bat}[k] - \Delta E_{gain}[k].\eta_{prop}{}^{-1}, \quad if\ \Delta E_{gain}[k] < 0 \quad (8)$$

$$E_{bat}[k+1] = E_{bat}[k] - \Delta E_{gain}[k].\eta_{recup}, \quad if\ \Delta E_{gain}[k] \geq 0 \quad (9)$$

For each edge (i,j), assuming it takes n units of time to travel from node i to node j, total energy consumption e_{ij} is calculated using Equation 10 for discrete time step k.

$$e_{ij} = \sum_{I=k}^{k+n-1} (E_{bat}[I+1] - E_{bat}[I]) \quad (10)$$

Factors such as vehicle mass, speed, altitude changes and aerodynamics are taken into account in the energy calculations for each edge. Energy losses such as air resistance, rolling resistance and rotational resistance are also included in the model, enabling a comprehensive evaluation of energy consumption. In addition, the model allows energy recovery by considering the gains from regenerative braking in EVs. Therefore, some edges may have negative values, but this problem is solved in the path planning section. This validated model is also used in the traffic simulator SUMO (Simulation of Urban MObility) and is suitable for estimating energy consumption for various road types.

3.2. Multi-Criteria Decision-Making Approach using Analytical Hierarchy Process

In this study, AHP was used to assign weights to objective functions (total travel time, total energy consumed, and total travel distance) based on driver preferences (Vaidya and Kumar, 2006). The mentioned objective functions serve as criteria in the objective function decision-making process. AHP enables systematic decisions to be made by determining the relative importance of multiple criteria through a structured pairwise comparison process. Thus, the preferred routes by the driver were calculated with Dijkstra algorithm using the weights obtained as a result of the AHP.

The AHP begins with the normalization of criteria to ensure their comparability and integration into the decision-making process. The normalized values are calculated by Equation 11 using the maximum score method in Malczewski (1999), where x_i' represents the normalized value of the i^{th} criterion, and x_i is the original value of the given criterion and x_{max} represents the maximum score of the criterion across the network. The results are scaled to a range between 0 and 1.

$$x_i' = \frac{x_i}{x_{max}} \quad (11)$$

Original and normalized values of each criterion for an edge (v_i, v_j) are shown in Table 3. (t'_{ij}), (d'_{ij}), and (e'_{ij}) represents the normalized values of each criterion.
The pairwise comparison matrix is created using the Saaty Scale (Saaty, 1980), which helps assign relative value to each criterion with a $1-9$ scale representing linguistic terms presented in Table 4.

Table 3. Normalization of the Criteria

Criteria	Original	Normalized
Travel Time	$[0\ \infty)$	$[t_{min} / t_{max}\ \ 1], t'_{ij} = t_{ij} / t_{max}$
Travel Distance	$[0\ \infty)$	$[d_{min} / d_{max}\ \ 1], d'_{ij} = d_{ij} / d_{max}$
Energy Consumption	$[0\ \infty)$	$[e_{min} / e_{max}\ \ 1], e'_{ij} = e_{ij} / e_{max}$

Table 4. Relative Importance Scale

Relative Importance	Scale
Equally important	1
Slightly more important	3
Important	5
Very important	7
Extremely important	9
Intermediate values	2,4,6,8

The pairwise comparison is given in Table 5. Each element of the matrix signifies the relative importance of one criterion compared to another according to driver preferences, with diagonal elements given a value of 1 to indicate equal importance when a criterion is compared to itself. For example, the linguistic term 'extremely important' is selected to compare travel distance with energy consumption in Table 5, represented with numerical value 9, which sets the importance of energy consumption over travel distance to 1/9.

Table 5. Pairwise Comparison of Criteria

	Travel	Energy	Travel
Travel Time	1	3	1/7
Energy Consumption	1/3	1	1/9
Travel Distance	7	9	1

The driver preferences in Table 5 were transformed into an overall priority weight vector through the following steps:

Matrix C is constructed from Table 5 as

$$C = \begin{bmatrix} 1 & 3 & 1/7 \\ 1/3 & 1 & 1/9 \\ 7 & 9 & 1 \end{bmatrix}$$

Then, the following Equation 12

$$\frac{C[i,j]}{\Sigma_{i=1}^{n} C[i,j]} \tag{12}$$

is applied to each cell of matrix C for normalization to create the following matrix D:

$$D = \begin{bmatrix} 0.1200 & 0.2307 & 0.1139 \\ 0.0399 & 0.0769 & 0.0886 \\ 0.8400 & 0.6923 & 0.7974 \end{bmatrix}$$

Then, the following Equation 13

$$\frac{\Sigma_{j=1}^{n} D[i,j]}{n} \tag{13}$$

is applied to matrix D to obtain the column vector U.

$$U = \begin{bmatrix} 0.1549 \\ 0.0686 \\ 0.7765 \end{bmatrix}$$

In this example, the column U represents the overall priority weights. The priority weight of the criteria travel time, energy consumed, and travel distance are $u_1 = 0.1549$, u_2=0.0686, and $u_3 = 0.7765$, where $\sum_{i=1}^{3} u_i = 1$.

A consistency check is performed as the last step of the AHP to ensure the weights are reliable. Consistency Ratio (CR) in Equation 14 is calculated, where λ_{max} is the largest eigenvalue of the matrix C, n is the number of criteria, and RI is a constant value depending on the number of criteria (e.g., $RI = 0.58$ for $n = 3$, $RI = 0.9$ for $n = 4$).

$$CR = \frac{\lambda_{max} - n}{RI \cdot (n-1)} \tag{14}$$

The value of CR should be less than 0.1 for consistency. In our example, it's calculated as 0.0708, showing that the pairwise comparison matrix is consistent and the AHP is reliable.

An edge weight W_{ij} on edge (v_i, v_j), $i \neq j$ represents the final objective function assigned to each edge in the road network. This calculated with Equation 15, where $(x_{ij}^{l})'(l = 1, 2, 3, \ldots, k)$ are the normalized criteria weights for the edge. This calculation incorporates the AHP-derived weights with the edge attributes from Phase 1, allowing for a weighted evaluation of each road segment considering driver preferences.

$$W(v_i, v_j) = W_{ij} = \sum_{l=1}^{k} (x_{ij}^{l})' u_l = (x_{ij}^{1})' u_1 + (x_{ij}^{2})' u_2 + (x_{ij}^{3})' u_3 \tag{15}$$

By incorporating these weighted evaluations, the AHP-based methodology ensures that the path planning process aligns with driver preferences while effectively balancing the multiple criteria.

3.3. Path Planning Algorithm

The Dijkstra algorithm resolves the problem of determining the shortest path from a source to a destination in a graph (Javaid, 2013). It is a greedy approach to solving the single-source shortest path problem. It finds the shortest path from a source node to all other nodes in a connected graph without negative weights and works efficiently for both directed and undirected graphs (Medak and Gogoi, 2018). This algorithm helps identify the shortest path by minimizing the total cost of the path implemented by the Python NetworkX library. The flowchart of the overall process of the proposed algorithm is given in Figure 1.

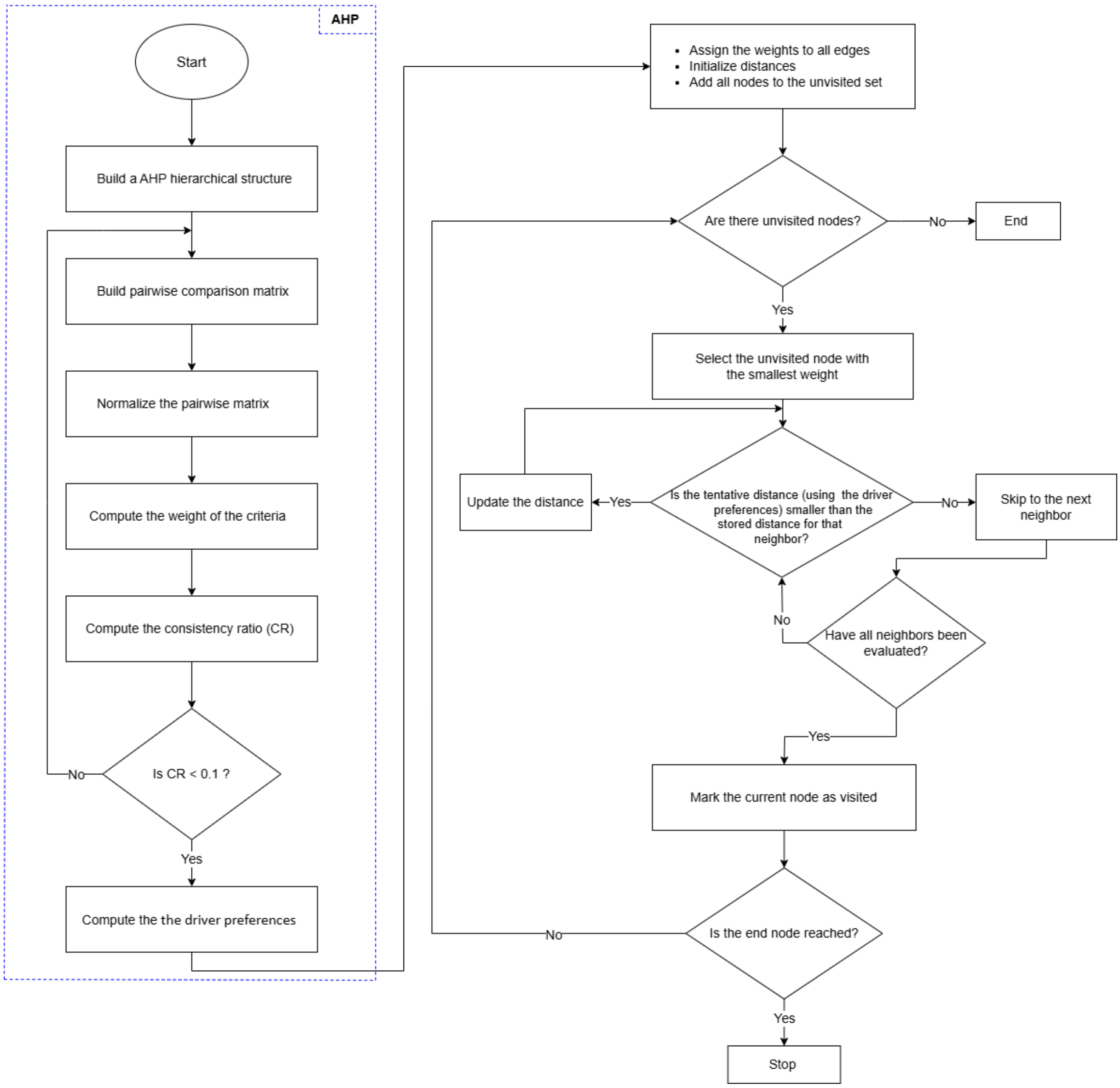

Figure 1. The Framework for the Proposed Path Planning Algorithm

The proposed method, illustrated in Figure 1, presents a multi-objective optimization approach for EV path planning by incorporating travel time, total consumed energy, and total travel distance into a unified path that aligns with driver preferences. Utilizing the AHP, it assigns weights to these objectives based on their relative importance and addresses negative energy weights through Johnson's technique. The final path is determined using the Dijkstra algorithm, ensuring an efficient and customized solution that aligns with the optimization objectives and driver preferences.

Energy consumption differs from other objectives since energy weights can be negative due to recuperation, and shortest algorithms, like Dijkstra algorithm (Dijkstra, 1959), cannot be directly applied. To solve this, Johnson technique (Johnson, 1977) is used to reweight the graph to eliminate negative weights while preserving the relative order of paths. Johnson technique deals with negative edge weights in a graph in several stages. First, a super-source node q is added to the graph, connecting it to all other nodes with edges of weight zero. Next, the Bellman-Ford algorithm (Bellman, 1958) is applied from this super-source node to compute the shortest distances ($h[v]$) from the super-source to all other nodes. The method terminates if a negative cycle is detected since the shortest paths are not well-defined. Following this, each edge (v_i, v_j) in the graph is reweighed using the formula $W'(v_i, v_j) = W(v_i, v_j) + h[v_i] - h[v_j]$, where $h[v_i]$ and $h[v_j]$ are the shortest path distances from the Bellman-Ford algorithm. This reweighting ensures that all edge weights $W'(v_i, v_j)$ become non-negative. After the reweighting, the super-source node is removed from the graph. This results in a modified graph that does not contain any negative edge weights. This enables the correct application of Dijkstra algorithm to determine the shortest paths.

4. Experimental Results

In order to test the proposed methodology, selected criteria for total travel time, total consumed energy, and total travel distance were individually visualized on a single map for better understanding. The experiment was conducted with limitations inside the Eskişehir Osmangazi University (ESOGU) campus area, as shown in Figure 2, where start and end points were selected to represent three different paths.

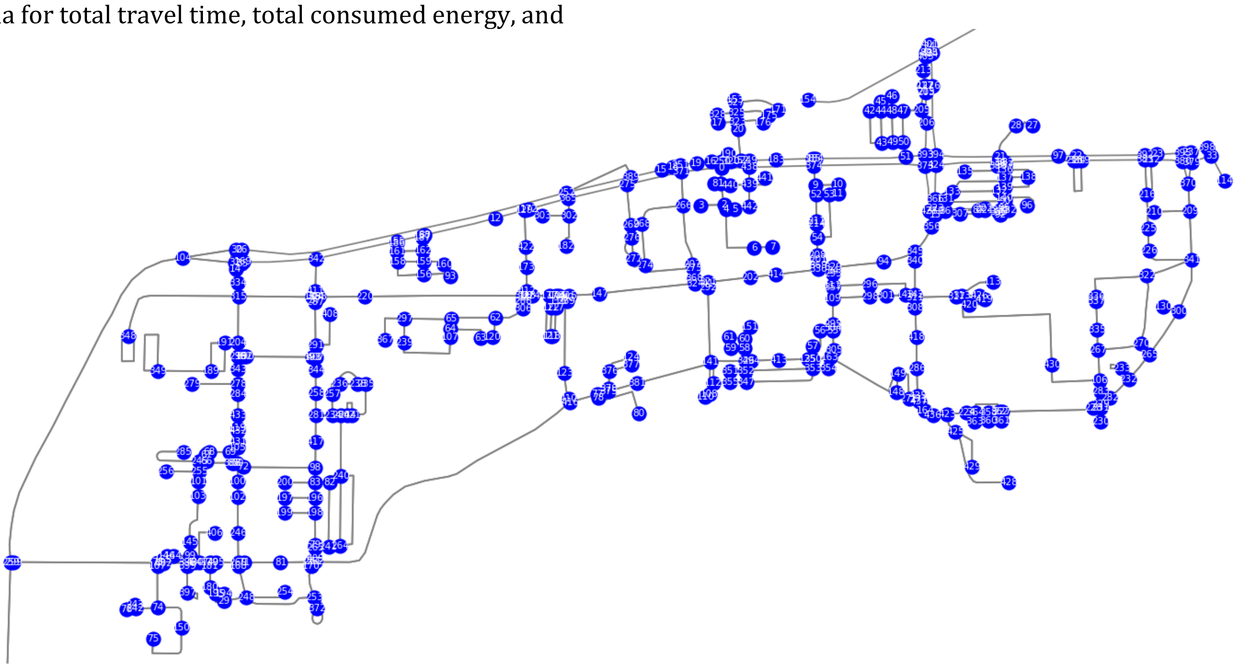

Figure 2. The Graph of the Eskişehir Osmangazi University

The visualization was created using Folium, an interactive mapping library, and OSM, an open-source geospatial database. Figure 3 presents the visualized result of the Dijkstra algorithm based on a single criterion (total travel time, total travel distance, and total energy consumption), while Table 5 summarizes the numerical statistics for path for total time (Path-TT), path total distance (Path-TD), and path for total energy (Path-TE).

Table 5. Comparison of Paths Considering Three Criteria

Measured Criteria	Path-TT	Path-TD	Path-TE
Total travel Time (s)	216.978	246.576	225.576
Total travel Distance (m)	1382.4	1219.1	1256.9
Total Consumed Energy (Wh)	198.7	199.1	192.7

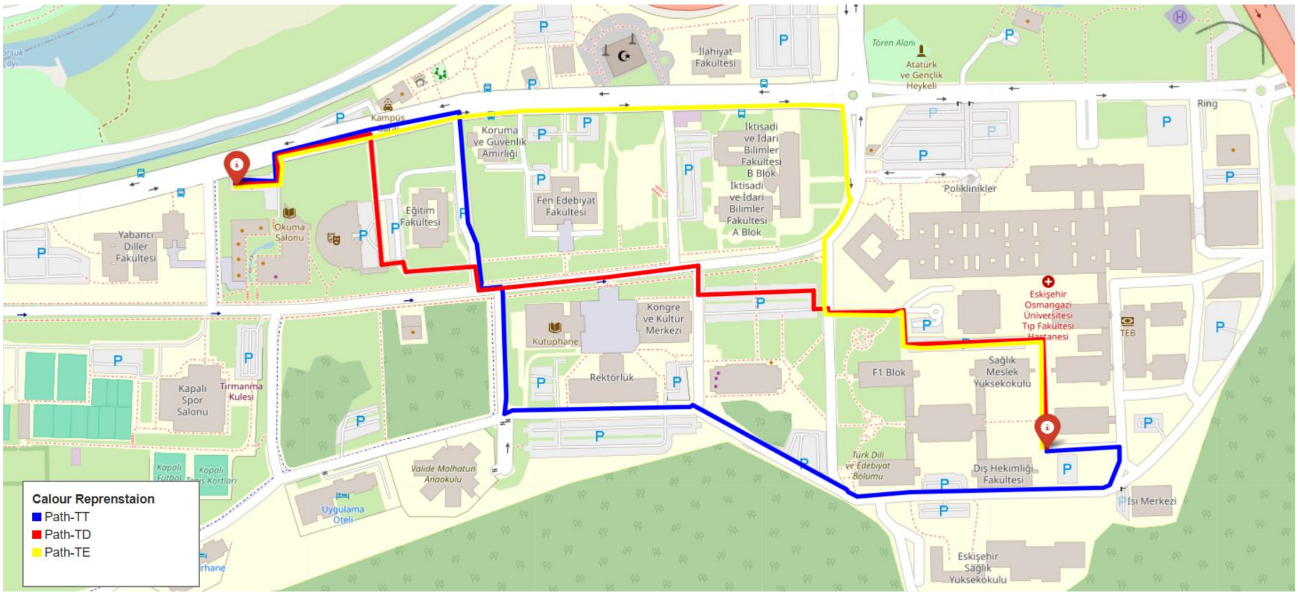

Figure 3. Paths considering single criterion

In the next phase, a driver preferred path was generated using AHP to combine multiple criteria based on driver preferences. According to the relative importance assigned to each criterion, travel distance was found to be the most important, followed by travel time and energy consumption. The priority weight of the criteria travel time, energy consumed, and travel distance were $u_1 = 0.1549$, u_2=0.0686, and $u_3 = 0.7765$. These weights were then integrated into Dijkstra algorithm to determine the driver preferred path, and the visualized result is presented in Figure 4.

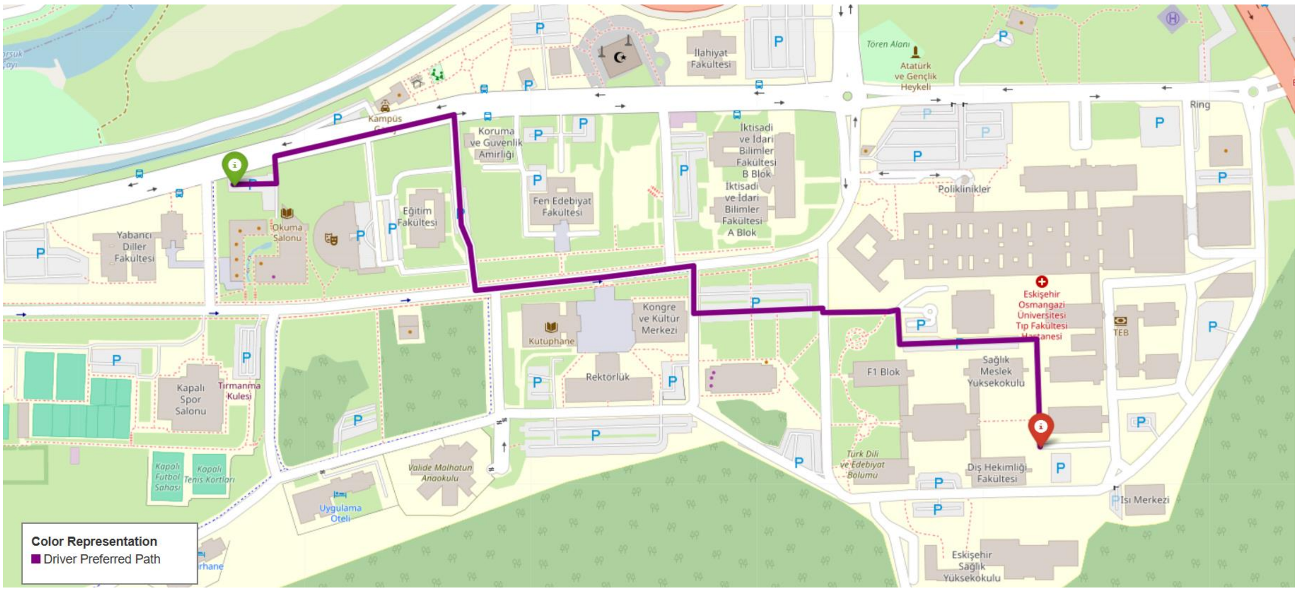

Figure 4. The Final Path Integrating Driver Preferences

The driver preferred routing process was shown to create unique paths compared to all three single criterion paths even within a small testing area. The length of the path is 1232.7 meters, energy consumption is 195.4 Wh and travel time is 231.576 seconds. With these results, it is shown that our proposed method offers unique and effective results in line with the driver preferences by considering multiple criteria.

5. Conclusion

A path-planning approach that can integrate driver preferences within the EV context is studied in this paper. The proposed algorithm combines total travel time, total travel distance, and total energy consumption in a single scope while also addressing the unique preferences of EV drivers via AHP. Dijkstra algorithm augmented with Johnson's technique to handle negative energy weights results in efficient and practical path planning. Experimental results show that the proposed methodology fulfills expectations for both single and multi-criteria routing and is capable of generating balanced paths by driver preferences. This algorithm, tested at ESOGU campus, has demonstrated its capability in EV routing scenarios. ESOGU campus is a relatively small area and may not fully reflect large-scale or high-traffic conditions. Future studies can create more comprehensive, dynamic and larger networks by including live traffic and charging station data and additional criteria such as road quality and usability. This will make the results more realistic and more suitable for practical applications.

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Authorship Contribution Statement

Mehmet Arıkan contributed to the experimental design and implementation, methodology, and manuscript writing. Sinem Bozkurt Keser and İnci Sarıçiçek contributed to methodology, manuscript writing, review, and editing. Ahmet Yazıcı contributed as the project leader by reviewing the manuscript and providing critical feedback.

Declaration of Competing Interest

The authors have no conflicts of interest to declare regarding the content of this article.

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