Elektrikli Araç Rotalama Perspektifinden Enerji Etkin Yol Analizi

Energy Efficient Path Analysis: From the Perspective of Electric Vehicle Routing

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Özetçe

Son zamanlarda enerji verimliliği ve sürdürülebilir enerji yönetimi, lojistik sektöründe büyük önem kazanmıştır. Bu doğrultuda, temiz ve yenilenebilir enerji kaynakları ile çalışması ve düşük karbon emisyonuna sahip olması gibi sebeplerle elektrikli araçların kullanımı günden güne artmaktadır. Elektrikli araçların yaygınlaşması ile doğru enerji tüketim modelini belirlemek üzerine çalışmalar da artmıştır. Bu çalışmada, elektrikli araçlar için bir enerji tüketim modeli kullanılmıştır. Kullanılan enerji tüketim modeli üzerinde hızın enerji tüketimine etkisi analiz edilmiştir. Analizler, gerçek bir ortamın Simulation of Urban Mobility (SUMO) ortamına aktarılması ile gerçekleştirilmiştir. Bu çalışma, enerji tüketimini en aza indirmek amacıyla yapılan elektrikli araç rotalama çalışmalarında ihtiyaç duyulan enerji tüketim verisinin graf üzerinde oluşturulması açısından değerli bir katkı sunmaktadır. Ayrıca, elektrikli araç rotalaması perspektifinden daha doğru enerji tüketimi tahminleri yapılması ve verimli elektrikli araç operasyonları gerçekleştirilmesi için gerekli verinin önemini vurgulamaktadır.

Abstract

Recently, energy efficiency and sustainable energy management have gained significant importance in the logistics sector. Consequently, the use of electric vehicles has been increasing day by day due to their operation with clean and renewable energy sources and their low carbon emissions. With the widespread adoption of electric vehicles, research on determining the appropriate energy consumption model has also increased. In this study, an energy consumption model for electric vehicles is used. This study analyzes the effect of velocity on energy consumption within the model. The analyses are conducted by transferring a real-life environment into the Simulation of Urban Mobility (SUMO) environment. This study offers a valuable contribution to the creation of energy consumption data on the graph, which is necessary for electric vehicle routing studies aimed at minimizing energy consumption. Additionally, it emphasizes the importance of accurate energy consumption predictions and efficient electric vehicle operations from the perspective of electric vehicle routing.

1. Introduction

Accurately predicting energy consumption is crucial for the efficient use of electric vehicles. With the increasing prevalence of electric vehicles, concepts such as energy efficiency, sustainability, and carbon emissions have become more significant in the transportation sector. Despite their eco-friendly nature, electric vehicles face challenges like charging time and driving range compared to fossil fuel vehicles. Particularly, in routing problems, the charging durations of electric vehicles has become a disadvantage compared to fossil fuel-powered vehicles. Therefore, the use of an energy consumption model that accurately predicts consumption has become more important.

The increasing adoption of electric vehicles has created a demand for models that can accurately predict energy consumption and driving range. A review of the literature reveals several prominent energy models [1]. These energy models have been developed to optimize the energy consumption of electric vehicles. Maia et al. developed a simulator to analyze the energy consumption of electric vehicles [2]. This simulator integrates electric vehicle models and elevation data into the SUMO simulation package, transforming the two-dimensional (2D) simulator into a three-dimensional (3D) simulator. The application enables more realistic simulations aimed at optimizing the energy consumption of electric vehicles and shows the importance of including elevation data for accurate energy predictions. Kurczveil et al. implemented an energy model and charging infrastructure in SUMO [3]. This work marks a significant step towards making the energy consumption of electric vehicles more efficient, highlighting the necessity of integrating charging infrastructure in simulation environments to reflect real-world scenarios more accurately. Fiori et al. developed a model to predict instantaneous energy consumption [4]. The model calculates energy consumption and estimates real-time braking energy recovery by taking vehicle velocity, acceleration, and road gradient as inputs. The model aims to optimize energy consumption under various driving conditions. The inclusion of real-time regenerative braking energy recovery significantly enhances the accuracy of energy consumption predictions, indicating the value of dynamic input factors in modeling. The inclusion of real-time braking energy recovery significantly enhances the accuracy of energy consumption predictions, indicating the value of dynamic input factors in modeling. Sagaama et al. evaluated the performance of the existing energy model in the SUMO simulation environment [5]. This study examines how accurately the model predicts energy consumption under different road conditions and traffic densities. The findings reveal that traffic density and road conditions have a profound impact on energy consumption, emphasizing the need for adaptable models that can account for variable traffic scenarios. It is clear that traffic density and road conditions significantly influence energy consumption, highlighting the necessity for flexible models. Perger and Auer presented a model for energy-efficient route planning that considers specific factors such as topography and battery life [6]. The research analyzes the effects of various road conditions and gradients on energy consumption and serves as a critical tool in developing route planning strategies to optimize energy consumption. The study emphasizes the importance of topography and gradient changes in route planning strategies and confirms the necessity of including these factors in energy models. These analyses underscore the necessity of incorporating diverse factors to create more robust and efficient energy models.

The studies in the literature emphasize the importance of developing route planning strategies and energy models that minimize the energy consumption of electric vehicles. For electric vehicle users, it is crucial in route planning to calculate how far the vehicle can travel with its current State of Charge (SoC). Using an appropriate energy consumption model can provide accurate information to electric vehicle users on this issue. The energy model used in this study calculates the energy consumption of an electric vehicle using parameters such as vehicle velocity, road gradient, and regenerative braking. Additionally, the energy consumption of electric vehicles is calculated as the result of total energy consumption from various components. The experiments are conducted using the SUMO application for a real-world environment. Calculation of energy consumptions for each road segment (edge) is done on the constructed map, and based on these calculations, the Dijkstra algorithm is used to obtain the paths between points with minimum energy consumption. This approach aims to optimize energy consumption and enhance operational efficiency in terms of Electric Vehicle Routing Problems (EVRP).

2. Method

The existing energy models used in the SUMO simulation environment employ various parameters and algorithms to predict the energy consumption of electric vehicles. Kurczveil et al. [3] designed a model that integrates variables like velocity, acceleration, deceleration, and road gradients to assess energy usage. These elements are crucial as they directly impact energy demands under varying driving scenarios, yielding more precise consumption forecasts. Fiori et al. [4] adopted a similar approach, utilizing analogous parameters to gauge real-time energy consumption while incorporating energy recovery mechanisms, which are pivotal for enhancing EV efficiency through regenerative braking. This study is based on the energy model used in SUMO [3], [4], [5]. The model calculates energy consumption using parameters such as vehicle velocity, road gradient, and regenerative braking. These parameters allow for more realistic and reliable energy consumption estimates as they encompass the primary dynamics affecting vehicle energy use. Additionally, the battery capacities and charging times of electric vehicles are incorporated into the model, which is critical for understanding the vehicle's driving range and planning charging stops effectively. The energy consumption of electric vehicles is formulated as the result of total energy consumption, which is calculated by considering the components of potential energy, kinetic energy, rotational energy, air resistance, rolling resistance, radial resistance, and constant power consumption. Potential energy (Equation 1) is calculated as the energy expended against gravitational force when the vehicle moves on an inclined road. This energy is directly proportional to the vehicle's mass (m), gravitational acceleration (g), road gradient (θ), and vehicle velocity (v). Kinetic energy (Equation 2) arises from the change in the vehicle's velocity and is calculated considering the vehicle's mass (m) and the velocity change per unit time. Rotational energy (Equation 3) results from the velocity change of the vehicle's wheels and other rotating parts and is calculated using the mass of the rotating parts $m_{rot}$and the velocity change per unit time, expressed as $\frac{v^2-v^2{}_{last}}{\Delta t}$. Air resistance (Equation 4) is the energy resulting from the interaction with air as the vehicle moves and is calculated using the vehicle's frontal area A_{front}, air drag coefficient C_{drag}, and vehicle velocity (v). Rolling resistance (Equation 5) is the energy resulting from the interaction between the vehicle's wheels and the road surface and is calculated using the rolling resistance coefficient C_{roll}, vehicle mass (m), and velocity (v). Radial resistance (Equation 6) is the energy expended against centrifugal force when the vehicle makes a turn and is calculated using the radial resistance coefficient C_{radial}, vehicle mass (m), velocity (v), and turning radius (r). Constant power consumption (Equation 7) refers to the energy continuously consumed by the vehicle's electrical systems and other auxiliary equipment.

$$P_{potential} = m \times g \times \sin(\theta) \times v \tag{1}$$

$$P_{kinetic} = \frac{1}{2} \times m \times \frac{v^2 - v^2{}_{last}}{\Delta t} \tag{2}$$

$$P_{rotational} = \frac{1}{2} \times m_{rot} \times \frac{v^2 - v^2{}_{last}}{\Delta t} \tag{3}$$

$$P_{air} = \frac{1}{2} \times \rho \times A_{front} \times C_{drag} \times v^3 \tag{4}$$

$$P_{roll} = C_{roll} \times m \times g \times v \tag{5}$$

$$P_{radial} = C_{radial} \times m \times \frac{v^2}{r} \times v \tag{6}$$

$$P_{constant} = P_{constant\ intake} \tag{7}$$

2.1.Total Energy Consumption

Total power consumption is determined by P_{total} (Equation 8). These calculations include various parameters that change according to the vehicle's movement and road conditions. For instance, a vehicle moving on an inclined road consumes potential energy due to the gravitational force acting against its motion. When there is a change in velocity, kinetic energy consumption occurs, reflecting the energy required to accelerate or decelerate the vehicle. Rotational energy is expended with the rotation of the wheels and other rotating components, indicating the energy required to maintain the vehicle's motion. As the vehicle's velocity increases, both air resistance and rolling resistance also increase. Air resistance is a function of the vehicle's velocity and frontal area, while rolling resistance is influenced by the interaction between the vehicle's tires and the road surface. Radial resistance is considered when the vehicle makes a turn, representing the energy required to overcome centrifugal forces. Constant power consumption refers to the energy used by the vehicle's continuously operating systems, such as electronics and climate control. The sum of all these power components constitutes the vehicle's total power consumption, providing a comprehensive measure of the energy required for the vehicle's operation under varying conditions.

2.2.Energy Efficiency

The energy efficiency of electric vehicles varies based on factors such as propulsion and regenerative braking efficiencies. During acceleration, total energy consumption is related to the vehicle's propulsion efficiency $\eta_{propulsion}$ (Equation 9). This efficiency indicates how effectively the vehicle's motor uses energy to produce motion, and higher propulsion efficiency results in lower energy consumption for the same amount of acceleration. During regeneration, total energy consumption is calculated by multiplying it with the regeneration efficiency $\eta_{regeneration}$ (Equation 10). Regenerative braking allows for energy recovery when the vehicle brakes, reducing the vehicle's total energy consumption by converting kinetic energy back into stored electrical energy. During deceleration, energy efficiency is related to the regenerative braking efficiency $\eta_{recuperation\ deceleration}$ (Equation 11). In this case, the energy recovered during braking increases the overall energy efficiency, as a portion of the energy that would otherwise be lost is reclaimed. Consequently, total energy consumption is calculated considering all these efficiency factors, resulting in the final energy outcome (Equation 12).

$$P_{total} = P_{potential} + P_{kinetic} + P_{rotational} + P_{air} + P_{roll} + P_{radial} + P_{constant} \quad (8)$$

When accelerating:

$$P_{efficiency} = \frac{P_{total}}{\eta_{propulsion}} \quad (9)$$

When recuperating:

$$P_{efficiency} = P_{total} \times \eta_{propulsion} \quad (10)$$

Considering deceleration:

$$P_{efficiency} = P_{efficiency} \times \frac{1}{e^{\frac{\eta_{recuperation\ deceleration}}{|\alpha|}}} \quad (11)$$

$$E_{resulting} = \frac{P_{total}}{3600} \quad (12)$$

The comprehensive approach to energy efficiency highlights the importance of optimizing both propulsion and regenerative systems to minimize the energy consumption of electric vehicles.

3. Energy Efficient Path Planning

Vehicle routing problems are solved for various purposes. Specifically, in the EVRP, minimizing total energy consumption becomes significant. In this context, it is necessary to calculate the energy consumption of each road segment (edge) in the map for the routing algorithms. However, under different conditions, the factors affecting energy consumption can vary. Consequently, varying energy consumption values cause differences in paths. Therefore, energy-efficient path planning is crucial for optimizing the overall performance and sustainability of electric vehicles. For this purpose, in this study, the energy matrix has been calculated to minimize energy consumption between determined delivery points on the Eskişehir Osmangazi University (ESOGU) map. To create this matrix, initial energy calculations are performed for each road segment, and Dijkstra algorithm is applied using the obtained energy values. During energy calculations, factors such as vehicle velocity and road gradient are considered. The constructed energy matrix is obtained through the steps of data collection, energy calculation, and application of Dijkstra algorithm. In the data collection phase, all elevation data for the ESOGU map transferred into the SUMO environment, and consequently the slope values for each edge of the network, have been collected. Subsequently, the energy consumed during the traversal of each road segment is calculated by using the energy consumption model given in section 2. Finally, these energy values are processed using the *findRoute* method within the SUMO application to determine the routes with the least energy consumption for all designated points on the map (Figure 1).

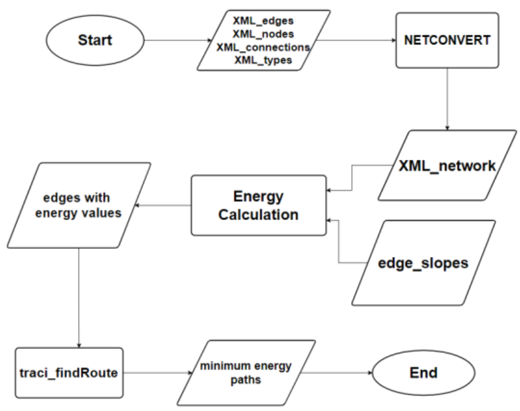

Figure 1: Path Generation Process

The matrix containing the energy consumption values between each of the designated points has been created using the paths determined by *findRoute* method within SUMO. The constructed energy consumption matrix is used for energy-efficient route planning. This matrix enables the identification of optimal routes that minimize energy usage, thus extending the vehicle's driving range. By incorporating detailed energy calculations, the matrix provides a robust foundation for making informed routing decisions that enhance the efficiency and sustainability of electric vehicle operations.

3.1.Test Environment

The test environment is created using the SUMO (Simulation of Urban Mobility) map of ESOGU (Figure 2). The graph $G = (V, E)$ represents this environment, where V denotes the set of nodes and E denotes the set of edges.

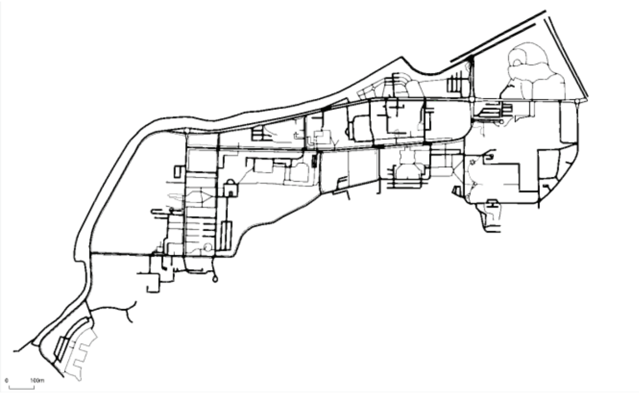

Figure 2: The representation of ESOGU Map in SUMO Environment

The nodes in the graph correspond to specific points within the ESOGU campus, encompassing various locations. The edges represent the road segments connecting these points, with each edge assigned an energy value calculated based on factors such as road gradient and vehicle velocity. The primary objective is to determine the most energy-efficient routes between these points. To achieve this, energy consumption calculations are performed for each road segment, considering the aforementioned factors. Subsequently, the Dijkstra algorithm is applied to these energy values to construct the energy matrix, identifying paths that minimize energy consumption. The data collection phase involves gathering slope data for all road segments within the SUMO environment of the ESOGU map, which is essential for accurate energy calculations during the traversal of each road segment.

Incorporating slope data and other relevant factors into the energy model ensures that the simulation closely mirrors real-world conditions, providing a robust basis for optimizing route planning. This approach helps achieve energy savings and contributes to the broader goal of enhancing the sustainability and efficiency of electric vehicle operations. The integration of these detailed elements allows for the development of more precise energy management strategies, resulting in reduced overall energy consumption and increased operational efficiency.

3.2.Experimental Results

Energy consumption models for electric vehicles encompass numerous factors, including vehicle velocity, road gradient, and regenerative braking. Understanding the effects of these factors is crucial for accurate State of Charge (SoC) predictions and overall energy efficiency. Although electric vehicles are generally less affected by road gradients compared to conventional vehicles, the impact of slopes on energy consumption is still significant. Traditional models often overlook the effect of road gradient, leading to estimation errors. The regenerative braking system, which allows for energy recovery during braking, plays a particularly crucial role in improving the efficiency of electric vehicles, especially in urban environments. In this study, various energy consumption matrices were constructed by varying vehicle velocity to understand its impact on total energy consumption. Specifically, energy matrices are created for vehicles moving at speeds of 15, 25, and 35 km/h within the ESOGU campus. Using the Dijkstra algorithm, matrices containing both the minimum distances between nodes and the minimum energy consumption paths at these three distinct average velocities were obtained. The routes generated for the total minimum distance and total minimum energy consumption objective functions were then compared (Table 1).

Table 1: Total Energy Consumption

Objective Function	Route	Total Distance (m)	Total Energy Consumption (kWh)		
			15 km/h	25 km/h	35 km/h
Min. Energy	$cs5 \rightarrow 31 \rightarrow 119 \rightarrow 113 \rightarrow 26 \rightarrow cs5$	6883	0.37960	0.53286	0.73446
	$cs5 \rightarrow 34 \rightarrow 13 \rightarrow 14 \rightarrow 24 \rightarrow 22A \rightarrow 45 \rightarrow cs5$				
Min. Distance	$cs5 \rightarrow 24 \rightarrow 22A \rightarrow 13 \rightarrow 14 \rightarrow 113 \rightarrow 26 \rightarrow cs5$	5923	0.39741	0.56132	0.77781
	$cs5 \rightarrow 31 \rightarrow 119 \rightarrow 34 \rightarrow 45 \rightarrow cs5$				

In Table 1, "cs5" refers to the depot. The electric vehicle starts from the depot, visits delivery points, and then returns to the depot. Route demonstrations include the depot and delivery points according to the respective objective function. For the minimum distance objective function, two routes (Figure 3) are obtained. In the example problem with ten delivery points, the total distance of the routes obtained for the minimum distance objective function is 5923 meters. The problem has also been solved for the minimum energy objective function. The total length of the routes obtained by minimizing the total energy consumption of electric vehicles is 6883 meters. Although the route obtained with a vehicle speed of 35 km/h for the minimum energy objective function (Figure 4) covers a longer distance of 6883 meters, it achieves a 5.58% reduction in energy consumption. This situation demonstrates the importance of considering energy consumption in route planning and shows that by optimizing energy usage, higher efficiency can be achieved even over longer distances. The study also aims to perform energy calculations not in real-time but using a pre-constructed energy matrix. This approach provides more efficient processing by reducing the computational load during simulations. By utilizing a pre-constructed energy matrix, the system can operate with significantly less resource consumption, ensuring smoother and faster computations. This method offers a practical solution for optimizing routes based on static factors, providing a balance between accuracy and computational efficiency. In the study, factors other than speed and road gradient are kept constant. The objective is to analyze the impact of speed and road gradient on energy consumption. The analysis results show that higher speeds generally increase energy consumption. Similarly, high-gradient road segments lead to higher energy consumption during climbing while becoming advantageous for energy recovery during descent. This study, which examines these factors, provides an understanding of the impact of gradients and particularly speed on energy consumption in electric vehicles. This theoretical analysis helps to lay the groundwork for future empirical studies and assists in improving energy models to enhance their accuracy and reliability.

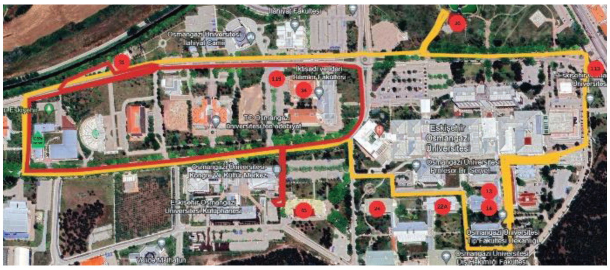

Figure 3: Routes for The Minimum Distance Objective Function

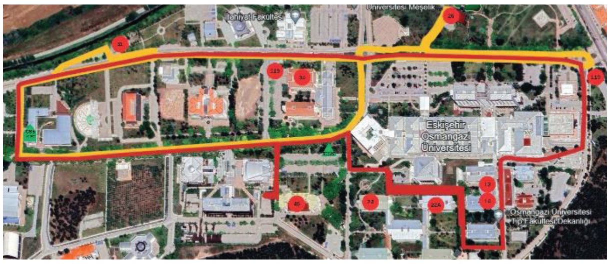

Figure 4: Routes for The Minimum Energy Objective Function

The analysis reveals that, despite the routes identified by the energy consumption matrix and the distance matrix often showing minor differences, significant observations can be made in terms of energy efficiency. Specifically, due to factors such as regenerative braking and varying slopes, routes that follow longer paths can still result in lower overall energy consumption.

4. Conclusion and Recommendation

In this study, the energy consumption model within SUMO is used to obtain the energy consumption of electric vehicles (EVs) between nodes. Energy calculations are performed for each road segment (edge) on the constructed map, and based on these calculations, the Dijkstra algorithm is applied to determine the minimum energy consumption paths between points. This approach aims to minimize energy consumption and enhance operational efficiency by analyzing the impact of speed variations. The test problem with ten customers is solved for both the total distance minimization and total energy consumption minimization objective functions. The trade-offs between these two objective functions are presented using analyses conducted in a real-world environment within SUMO. The study emphasizes the importance of considering the effects of road gradients and varying speeds on energy consumption for energy-efficient electric vehicle routing operations. The findings reveal that optimizing energy consumption, by leveraging regenerative braking and minimizing the impact of gradients, can lead to more sustainable electric vehicle operations. This approach not only extends the vehicle's driving range but also reduces the frequency of visits to charging stations, thereby enhancing overall efficiency. However, this study primarily focuses on energy consumption and distance while other critical factors such as travel time and environmental impacts, including rate of harmful gas emissions, have not been considered. These factors can be considered in order to provide a more holistic approach to sustainable transportation in future studies. Specifically, understanding the trade-offs between energy efficiency and travel time, as well as quantifying the reduction in harmful emissions, would offer deeper insights into the overall benefits of electric vehicle routing strategies. To further improve the accuracy and applicability of energy-efficient route planning, future studies will focus on integrating driver behavior patterns and acceleration factors into energy consumption models. Additionally, critical factors such as battery temperature, which can affect battery performance and energy consumption, are planned to be incorporated into the model. The impact of variable traffic conditions, especially stop-and-go traffic, on energy efficiency will be analyzed in detail. Furthermore, expanding data collection to include more diverse road conditions and vehicle types are expected to enhance the reliability of energy consumption models for more sustainable transportation solutions.

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