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Prediction of Electric Vehicle Mileage According to Optimal Energy Consumption Criterion

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Abstract

In the field of electric vehicle usage, an inherent challenge lies in the restricted mileage capacity prior to requiring a recharge, hindering broader acceptance of electric vehicles. To alleviate this concern, enhancing the comprehension of vehicle energy consumption and range plays a pivotal role in easing the anxieties of electric vehicle drivers. Within this context, a novel model-based predictive approach is introduced for estimating electric vehicle energy consumption. This method considers the vehicle's specific parameters, the road network's topology, and actual traffic conditions. Through the macro model of electric vehicle energy consumption, real-time summary data can be extracted using conventional map-based web services. By representing the road network as a weighted directed graph tailored to the energy consumption model, an algorithm aids in mileage optimization by determining the optimal path for immediate use. The resultant motion range from this approach offers improved precision and dependability in contrast to conventional strategies based on average consumption and distance.

Keywords: mileage; energy consumption; electric vehicle; adjoint graph; shortest path algorithm.

1. Introduction

The proliferation of modern electric vehicles (EVs) is impeded by various factors, despite their inherent advantages. Challenges such as limited mileage compared to internal combustion engine vehicles, sparse and uneven distribution of charging infrastructure, and the time required for recharging prompt drivers to meticulously plan their trips and opt for routes without intermediate charging stops. Expanding battery capacity faces constraints due to high costs and environmental repercussions from production and disposal processes. Consequently, the imperative of accurately predicting electric vehicle range with existing energy reserves in distinct road scenarios remains pertinent. Conventionally, the certified driving range ("passport" range) is determined under standard, typically gentle driving conditions, rendering it impractical for real-world trip planning. Conversely, "worst-case" mileage estimates based on peak energy consumption tend to be overly conservative for practical forecasting purposes.

Strategies that modify driving behavior to reduce energy consumption, such as eco-driving and eco-routes, present promising means to virtually extend electric vehicle ranges. Accordingly, ongoing development efforts aim to enhance energy efficiency and devise more pragmatic approaches to range prediction, tailored to specific operational contexts. Informing drivers with precise range estimations fosters better comprehension of energy usage and bolsters confidence in everyday electric vehicle utilization.

Accurate and context-aware forecasting hinges on comprehensive considerations of electric vehicle transmission characteristics and the nuances of road and transportation networks. Inaccurate energy consumption estimations often yield overly cautious range projections, needlessly escalating driver apprehension. Moreover, when forecasting energy utilization and driving ranges, it is crucial to delineate route options that enable drivers to reach their

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destinations within the operational range. Route selection significantly impacts energy expenditure; hence, neglecting this aspect can compromise range estimations. Despite its critical importance, route optimization is frequently overlooked in range prediction methodologies [1],[2].

The core of range prediction strategies lies in energy consumption estimation. Some studies address this issue through regression models at varying data aggregation levels [3]. Such approaches often lack the capability to relate modeling errors to the underlying physics of the problem. Moreover, the omission of road network features and traffic dynamics is common. Predictions of energy consumption can alternatively stem from physical models of vehicle components. For instance, in [4], the entire powertrain system is modeled to estimate energy consumption by forecasting instantaneous speed profiles and battery states. However, forecasting driving profiles based on historical data and standard driving cycles limits the method's applicability to unfamiliar road networks and routes. In [5], two prediction strategies are presented using battery voltage monitoring; however, this technique fails to account for acceleration influences on energy consumption along with road topology and traffic control device impacts. These considerations, as highlighted in [6], are crucial for precise energy consumption evaluations, particularly in urban road networks.

The studies mentioned above focus on range prediction but do not incorporate visual range display on maps. Correspondingly, they do not address the relationship between distance and road network topology. In [7], the method calculates energy consumption based on a predefined standard profile and claims to compute real-time energy consumption across all feasible routes originating from the current position using a topological search algorithm.

Comprehensively exploring all potential routing paths in a graph poses an NP-hard problem. However, detailed insights into the wayfinding technique, an approximate energy consumption model, and its reliance on road network specifics are lacking. In [8], a regression method is proposed for estimating range in terms of driving distance leveraging a combination of historical and real-time traffic data. The distance range is then visually represented on a map using an Euclidean method (e.g., a circular representation with a radius equal to the calculated range) or a polygon. Notably, this approach disregards road network topology considerations.

In the literature, a method proposed by the authors in [9] introduced a wider search algorithm to apply achievable functions while considering energy constraints; however, this method fails to ensure optimal energy consumption, leading to a conservative estimation of the operational range based on current road routes to the destination. Furthermore, the energy consumption model employs a standard driving cycle to replicate speeds in urban settings, thereby lacking predictive accuracy based on real-time traffic data. In a related study [10], the importance of selecting eco-friendly routes to determine range is emphasized; nevertheless, the simplistic energy consumption model and road network representation hinder satisfactory accuracy in urban and suburban contexts. Similarly, in [11], the author proposed driving range forecasting based on optimal energy routing but cautioned that the chosen energy consumption model might compromise accuracy due to varying road conditions and speed simulations.

This study endeavors to enhance the precision of electric vehicle mileage prediction methods. Firstly, a comprehensive model of the electric vehicle energy system is introduced, encompassing auxiliary electricity demand and the impact of road network characteristics on energy usage. Secondly, considerations are made for traffic conditions and traffic management systems, especially vital in urban and suburban settings. Additionally, a network modeling approach utilizing an adjacency graph is proposed to accurately calculate energy consumption considering accelerations and maneuvers (e.g., turns at intersections). The driving range estimation involves optimizing energy-efficient routes (eco-routes) in the adjacency graph using a modified Bellman-Ford algorithm, ensuring both solution optimality in negative energy cost scenarios and reducing computational complexity significantly. By explicitly incorporating eco-routes, this strategy distinguishes itself by simultaneously integrating road features into energy consumption calculations without resorting to average consumption or worst-case driving distance estimations, resulting in a less conservative and more precise motion forecast. Moreover, this approach facilitates a more precise depiction of the driving range on maps, delineating inaccessible regions within the range.

The structure of the article is as follows: Section II provides a detailed account of energy consumption, the road network model, and the methodology for computing the energy-optimal driving range. Section III discusses the experimental results, while concluding remarks are outlined in Section IV.

2. Problem formulation

The objective of this study is to enhance the energetically optimal prediction of power reserve for electric vehicles by utilizing macroscopic data pertaining to the road transportation network. In addition to this network data, other influential factors include vehicle-specific parameters, the source location of the vehicle, and the current state of charge (SOC), which can be automatically retrieved from the vehicle itself. The proposed approach aims to compute the ideal energy consumption required to reach the starting point of all potential destinations within the designated area. This method allows for a more favorable estimation of the worst-case average energy consumption across the road network and provides a clearer insight into the energy profile of the road network. The operational framework of this procedure is illustrated in Figure 1.

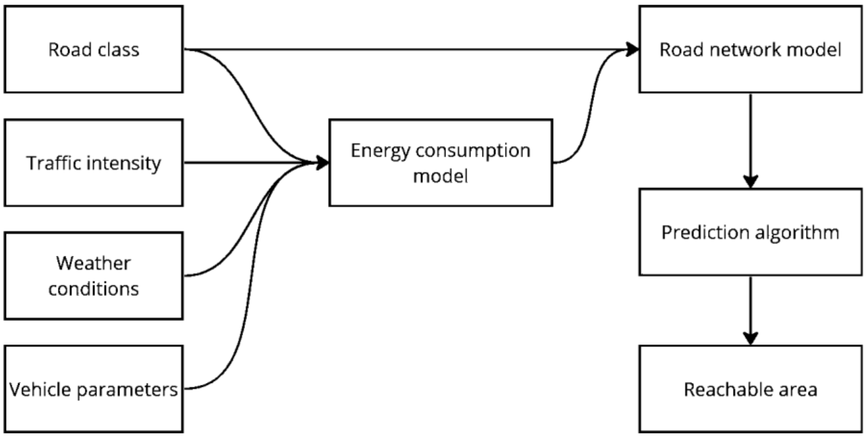

Fig.1. Prediction algorithm structure.

2.1. Energy consumption model

Considering that the proposed methodology focuses on predicting a vehicle's operational range through the utilization of macroscopic internet data (such as average speed, altitude, traffic light locations, etc.), it becomes essential for the energy consumption model to encapsulate the vehicle's interaction with the road infrastructure. The energy consumption model delineated here accounts for both the vehicle's intrinsic characteristics and the driving speed profile contingent upon environmental variables, a nuanced feature that bears particular significance in urban road networks.

Nevertheless, as delineated in the research by [6], the complexity inherent in the topological and traffic data housed within the network precludes the construction of a time-varying energy consumption model. The primary objective, therefore, is to characterize the vehicle model as a function of its displacement. The ensuing discourse encapsulates the fundamental equations underpinning the model.

The speed on the road section *i* must be constant and equal to the average value $\bar{v}_i$. Longitudinal dynamics can be expressed by the equation of the vehicle on the road section *i* as:

$$m\dot{v}_x = F_T - R - mg\sin\alpha \;, \tag{1}$$

where *m* is the mass of the car; $\dot{v}_x$ is the acceleration in the longitudinal direction; F_T is the traction force transmitted to the car from the side of the wheel's contact with the road; *R* is the force of aerodynamic resistance; *mg* is the force of gravity; α is the angle of inclination of the road to the horizon in the longitudinal direction.

In steady motion, there is no average acceleration. The average drag force on section i can be approximated by a second-order polynomial. Then for the average traction force on the wheels we get:

$$\bar{F}_{T,i} = a_2\bar{v}_i^2 + a_1\bar{v}_i + a_0 + mg\sin\alpha_i \;, \tag{2}$$

where the coefficients a_0, a_1 , and a_2 depend on vehicle characteristics.

The torque required from electric motor can be calculated as:

$$\bar{T}_{m,i} = \bar{F}_{T,i} \cdot r \cdot \rho_t^{-1} \cdot \eta_t^{-\mathrm{sign}(\bar{F}_{T,i})}, \tag{3}$$

where *r* is the wheel radius; ρ_t and η_t are the gear ratio and efficiency, respectively.

In the stationary mode, the engine speed is also kept constant. Corresponding angular velocity is:

$$\overline{\omega}_i = \bar{v}_i \cdot \rho_t \cdot r^{-1}. \tag{4}$$

The range of torques created by the electric motor is limited by the maximum torque $T_{m;\min}(\omega_i)$ and the minimum torque $T_{m;\max}(\omega_i)$. The latter is a negative moment created by the engine in generator mode (recovery mode). During braking, if the required braking torque is smaller in absolute value than the torque $T_{m;\min}(\omega_i)$., the vehicle is slowed down only by regenerative braking, otherwise the mechanical brakes will also be applied. It is important to note that the indicated limit moments are functions of the motion mode.

The power available on the shaft of the electric motor, in the presence of a regenerative braking mechanism, can be written as follows:

$$\bar{P}_{m,i} = \bar{T}_{m,i} \cdot \omega_i; \qquad T_{m;\min} \leq \bar{T}_{m,i} \leq T_{m;\max} . \tag{5}$$

Finally, considering the efficiency of the electric drive, the required power can be rewritten as follows: s:

$$\bar{P}_{b,i} = \bar{P}_{m,i} \cdot \eta^{-\mathrm{sign}(\bar{P}_{m,i})}, \tag{6}$$

where η is the overall efficiency of the electric drive.

To increase the accuracy and reliability of the energy consumption estimate, it is important to consider the auxiliary power requirements as well. For example, especially for electric vehicles, the power consumed by the air conditioning system in the cabin has a significant impact on the total energy consumption, and this impact increases with the duration of the trip and the increase in the temperature difference between the environment and the cabin.

The auxiliary power consumption can be simply modeled as a monotonic function of the ambient temperature T_{ext}:

$$P_{aux} = f(T_{ext}) \tag{7}$$

As a result, battery power consumption is:

$$\bar{E}_{b,i} = \left(\bar{P}_{b,i} + P_{aux} \right) \cdot \tau_i , \tag{8}$$

where $\tau\_i = l_i \cdot \bar{v}_i^{-1}$ is the travel time on section *i* of the road of length l_i when moving at an average speed of $\bar{v}_i$.

In order to take into account the effects of acceleration and to improve the model and estimation of energy consumption, it is assumed that the trip on each road segment consists of two phases: a cruising phase at a constant speed v_i and an acceleration phase to go from v_{i-1} to v_i . Energy consumption associated with a change in speed at the intersection of two road sections is defined as:

$$E_{\mathrm{jump},i-1,i} = \int_0^{t_{\mathrm{jump},i-1,i}} \left(\bar{P}_{b,i-1,i} + P_{aux} \right) dt , \tag{9}$$

where the battery energy consumption $\bar{P}_{b,i-1,i}$ is derived similarly to equations (2)-(6) from the traction force on the wheels.

The traction force on the wheels defined as:

$$F_{w;i-1;i} = ma + a_2 \bar{v}_{i-1;i}^2(t) + a_1 \bar{v}_{i-1,i}\,(t) + a_0 . \tag{10}$$

where *a* is the constant acceleration.

The law of speed change in the transition section is assumed to be linear:

$$v_{i-1;i}(t) = \bar{v}_{i-1} + \mathrm{sign}(\bar{v}_i - \bar{v}_{i-1}) , \tag{11}$$

where $\bar{v}_{i-1}$ is the constant speed at the entrance section of the road; $\bar{v}_i$ is the constant speed at the exit section.

The change in speed is performed over a period:

$$t_{\mathrm{jump},i-1,i} = \frac{\bar{v}_i - \bar{v}_{i-1}}{\mathrm{sign}(\bar{v}_i - \bar{v}_{i-1})\, a} . \tag{12}$$

As mentioned earlier, the limitation of this assumption is that the speed fluctuations on the road section are neglected, which can lead to errors. However, modeling the actual acceleration on a road section seems unrealistic at the level of route planning, as it is highly dependent on local traffic conditions and is therefore often spontaneous and unpredictable [12].

Disturbances in speed and acceleration profiles are caused not only by traffic, but also by infrastructure. Road infrastructure elements such as traffic lights, intersections and turns can cause stops or significant delays. Therefore, when information about the position of these elements is available, the level of energy consumption with acceleration in (9) should be changed. For example, the change in speed between two sections of the road connected by a mandatory stop sign will be modeled as two different transitions: the first transition is from v_{i-1} to 0, the second is from 0 to v_i . Therefore, the energy consumption in the section of the speed change at the intersection can be divided into:

$$E_{\text{jump},i-1,i} = \int_0^{t_{\text{jump1},i-1}} \left(\bar{P}_{b1,i-1} + P_{aux} \right) dt + \int_0^{t_{\text{jump2},i}} \left(\bar{P}_{b2,i-1} + P_{aux} \right) dt \,, \tag{13}$$

where the speed change in the first term is modeled as $v_1(t) = \bar{v}_{i-1} - at$; the execution time of the first transition process is $t_{\text{jump},1} = \bar{v}_{i-1}a^{-1}$; the speed change in the second term is modeled as $v_2(t) = at$; the execution time of the second transient process is $t_{jump2;i} = \bar{v}_i a^{-1}$.

Finally, the total energy consumption of road section *i* can be expressed as:

$$E_{b,i} = \bar{E}_{b,i} + E_{\text{jump},i-1,i} \,. \tag{14}$$

2.2. Road network model

The road transport network can be modeled as a graph $G = (V;\, A)$, where *V* is the set of road intersections (or vertices) with the number of *n*, and *A* is the set of road segments (or arcs) with the number of m. Let's define the weighting function $w\colon A \to W$, which associates each arc of the graph with a weighting factor. In this paper, the weight factor of each arc of the traffic network modeling graph is determined according to the energy consumption in equation (14).

The primary challenge in graph modeling of road networks lies in adequately addressing accelerations during the traversal between adjacent graph arcs. Notably, nodes in a graph with multiple input arcs present a critical consideration due to potentially divergent velocities v_{i-1}, leading to varying energy requirements $E_{jump;i}$. This variability impedes the straightforward assignment of a consistent energy value to each graph arc, underscoring the inadequacy of graph *G* in accommodating accelerations. To overcome this challenge, a more refined approach involves modeling the road network through an adjacency graph, which better captures the nuances of accelerations and improves the accuracy of energy consumption estimations. An adjacent graph $L(G)$ of a graph *G* has as vertices an arc of *G*, and two nodes of $L(G)$ are adjacent when the corresponding links of *G* are adjacent. The degree identifier id (n_j) of the node $n_j \in V$ is the number of links included in n_j, while its output degree $\text{od}(n_j)$ is the number of links leaving n_j.

Let $G = (V; A)$ be a graph with *n* nodes and *m* arcs as before. Then$L(G) = (V^*\,; A^*\,)$ is an adjoint graph with $n* = m$ nodes and $m^* = \sum_{j=1}^{n} [\text{id}(\text{n}_j)\ \text{od}(\text{n}_\text{j}\,)]$ arcs. Each link $i \in A$ of the original graph *G* becomes a node $i \in V^*$ of the connected graph $L(G)$. We can define, as before, the input degree $\text{id}(i)$ and the output degree $\text{od}(i)$ for the node $i \in V^*$.

We define the weight function for the arcs of the connected graph $w^* : A^* \to W^*$, where the weight of each link $k \in A^*$ is:

$$W_k^* = \begin{cases} E_{b,i} + E_{jump,i-1,i}, & \text{if } \text{id}(i-1) \neq 0 \ ; \\ E_{b,i} + E_{jump,i-1,i} + E_{b,i-1}, & \text{if } \text{id}(i-1) = 0 \,. \end{cases} \tag{15}$$

Thus, the connected graph $L(G)$ allows us to correctly assign a unique energy cost to all possible maneuvers in the original graph *G*.

2.3. Shortest path algorithm

The challenge of determining the optimal driving range for electric vehicles can be viewed as a Single-Source Shortest Path (SSSP) problem on a road network simulation graph. This directed and cyclic graph is characterized by connectivity constraints, one-way roads, and sparse connectivity denoted by the sparse incidence matrix representing the network.

Electric vehicles and energy recovery considerations introduce the possibility of weighing graph links with negative costs. However, negative weights on a cyclic graph can lead to negative cycles, an impractical scenario where a vehicle infinitely regenerates energy by cycling through road sections endlessly. To address this concern, the modeling approach assesses energy consumption at each link interface depending on actual maneuvers, ensuring the integrity of energy calculations.

Consequently, the SSSP algorithm operates on a directed cyclic weighted graph with negative values. The Belman-Ford Algorithm (BF) is a well-established solution for optimal pathfinding on such graphs, offering a computational complexity of $O(n \times m)$ where n denotes nodes and m signifies arcs. When executed on the adjacency graph $L(G)$, the BF algorithm maintains a complexity of $O(n \times m)$.

In real-world applications, large road networks demand swift computation times unsuitable for user-centric or real-time scenarios. A modification of the standard BF algorithm incorporates an early termination condition during iterative runs, enhancing efficiency without altering worst-case performance. Demonstrated on road network models generated from the CARLA modeling system, varying calculations compared the standard BF algorithm's runtime against the modified version implementing early termination. Results displayed in Table 1 highlight computational time distinctions based on the number of iterations (n, k), providing insights into operational efficiencies under different graph resolutions.

This is clear that this version of the BF algorithm is an acceptable approach for real-time use.

Table 1. Belman-Ford algorithm efficiency.

	Graph 1	**Graph 2**	**Graph 3**
n	4169	50841	158478
n^*	7460	100203	191950
m^*	15267	225772	472367
T_{BF}	2.71 s	397.14 s	1513.06 s
k	101	344	263
T_{BFopt}	0.073 s	1.65 s	2.56 s

2.4. Energy reachable area

The Single-Source Shortest Path algorithm facilitates the determination of optimal routes from the initial vertex to all other nodes within the graph. This characteristic lends itself to identifying reachable destinations based on specified energy consumption levels, which can either be designated by the driver or derived from the current and target battery state of charge. The travel range obtained via SSSP is deemed optimal as it assures reachability to every node within the range through the shortest path originating from the source. Notably, as the graph is energy-cost weighted, nodes within the energy management range are accessible via eco-friendly routes.

This method exhibits a commendable level of precision in estimating electric vehicle power range. Unlike approaches that exclusively outline the polygonal driving range curve, this strategy enables the scrutiny of energy consumption attributes within the range, coupled with assessing the region's connectivity. Essentially, ensuring simple connectivity verifies accessibility of nodes within the range; failure to meet this criterion implies certain nodes remain unattainable even with eco-route assistance.

Moreover, this approach seamlessly extends to computing closed (round-trip) routes, a pertinent consideration for electric vehicle users necessitating return trips for battery recharging. Addressing the reachability of specific points with a mandatory return to the starting location is efficiently handled through the shortest path problem with return conditions. This task is effectively executed by operating the Bellman-Ford algorithm on a graph featuring reversed arcs, with the initial point designated as the destination for the return trip calculation.

3. Simulation results

The mileage prediction technique described in this paper presents several advantages over methods based on average energy consumption and/or distance-based driving range. In particular, the use of this method leads to less conservatism in forecasting.

The conducted experiments are aimed at demonstrating that the presented strategy allows to correctly fix the important characteristics of the power reserve for electric vehicles:

- The range of movement may be asymmetric with respect to the origin of the coordinates.
- The area of the driving range may not be simply connected.
- Auxiliary power consumption can have a significant effect on the energy range.
- Round trip distance can be predicted considering the asymmetry with respect to the origin of the coordinates.

Computational experiments were conducted on the road network of the virtual city of Sun City in the CARLA simulation system. As can be seen from Table 1, the graph associated with this road network includes about 130,000 nodes and 159,000 arcs, resulting in an adjacency graph with approximately 390,000 links. The adjacent graph has been weighted with the energy costs associated with normal weekday traffic during peak hours. The parameters of the electric vehicle used are given in Table 2.

Table 2. Test vehicle parameters.

Description	**Parameter**	**Value**
Total mass	m	1200 kg
Wheel radius	r	0.32 m
Gear ratio	ρ_t	9.7
Transmission efficiency	η_t	0.97
Acceleration	a	1.6 m/s^2
Coefficient 0	a_0	178.4 N
Coefficient 1	a_1	0
Coefficient 2	a_2	0.3 m/s^2
External temperature	T_{ext}	18°C
Additional power	P_{aux}	500 W
Electric drive efficiency	η_b	0.82

Typical EV range estimation strategies are based on assumptions about average energy consumption per kilometer. This "average" power consumption often corresponds to the worst-case consumption, i.e. a conservative estimate will be obtained, which is then used to calculate the range in terms of distance.

The assumption of average consumption does not allow us to properly consider the features of the real road network and possible routes. In addition, the transformation of the movement range in the distance reference system leads to a significant loss of accuracy.

In fact, it can be demonstrated that the energy driving range can be significantly asymmetric with respect to the starting point due to the characteristics of the road profile and traffic conditions in the transport network.

In the experiment, the proposed range calculation strategy is compared with a typical approach based on average energy consumption and the corresponding driving range radius in terms of distance. In the experiment, a conservative average energy consumption of 0.18 kWh/km was chosen (the value corresponds to the typical consumption of electric vehicles [11]). The available energy capacity is set at the level of 1 kWh. The chosen average energy consumption translates to a radius of 5.5 km, which corresponds to a symmetrical range. This is especially true in urban road networks, where the density of road infrastructure is quite high. However, this approach neglects such important factors as road class, traffic conditions, and the type of route used.

Our strategy can consider all these aspects and any destination within the energy range can be reached by an eco-route. Obviously, the reach range is asymmetric with respect to the starting point due to the presence of hilly terrain on the road and different levels of energy consumption depending on the external conditions. In our case, the range of energy movement ranges from a minimum of approximately 5 km to a maximum of 11 km.

When assessing the range of an electric vehicle, factors influencing energy consumption specific to the region are frequently disregarded. The ensuing experiment endeavors to underscore that the energy consumption characteristics within the vehicle's operational range may not adhere to fundamental properties like convexity and simple connectivity. Specifically, it is plausible that this region lacks simple connectivity, implying certain destinations within the coverage area are unattainable with the current battery charge level. The proposed methodology adeptly pinpoints these critical zones that remain inaccessible even through eco-routing. Through our experimental analysis, we identified three impassable areas necessitating energy outlay beyond the battery's indicated charge level. These regions manifest as spatial "holes" within the energy range and align with distinctive road features such as hills or densely populated areas. Anticipating the presence of such regions within the driving zone is crucial. For instance, an electric vehicle driver seeking a charging station would be wise to steer clear of stations situated in these critical zones, notwithstanding their apparent proximity within driving range.

The necessity of auxiliary power, particularly for operating an on-board cooling/heating system, can exert a substantial influence on an electric vehicle's energy reserve.

In the previous experiments, as outlined in Table 2, an ambient temperature of 18 degrees Celsius necessitated around 400 W of auxiliary power (i.e., cooling/heating system deactivated). Subsequent experimentation sought to demonstrate the notable impact on the driving range when ambient temperatures are raised, such as to 30 degrees Celsius. Under this condition, activation of the cooling system is anticipated, leading to an auxiliary power requirement scaling up to 2000 W.

The simulation results indicated a substantial reduction in the area encompassed by the new polygon, symbolizing the range coverage with the active cooling system. Specifically, this area decreased by approximately 65% compared to the range when the cooling system was inactive. In the most extreme scenario, the distance covered diminished by about 50%, aligning with findings from other studies [10]. Notably, a more pronounced reduction in range was observed for longer journeys within the section analyzed.

The experiment showed that the range of reach can have a significant asymmetry due to the peculiarities of the road profile and the characteristics of the road network. Our strategy, as discussed earlier, can also be used to calculate the round-trip distance. The simulation results show that some destinations beyond the travel range become accessible, provided that the destination of the trip is the starting point. This result shows that the proposed strategy is able to capture the energy consumption properties of different travel directions taking into account energy recovery in hilly terrain.

4. Conclusion

A new range prediction strategy for an electric vehicle is proposed. The technique uses aggregated road map data and vehicle parameters fed into the EV's energy consumption model to estimate energy consumption during any trip. The road network is represented as a directed connected graph. A modified algorithm for finding the energetically optimal route on the graph starting from the current position of the vehicle is applied. Consideration of the energetically optimal path for determining the range of motion is an improvement over standard method. The resulting range is more accurate due to the consideration of the specific characteristics of the road network, and therefore less conservative.

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Прогнозування пробігу електромобіля за критерієм енергетичної оптимальності

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Анотація

Обмежений пробіг без заряджання є однією з головних перешкод до широкого розповсюдження електромобілів. Краще розуміння енергоспоживання автомобіля та запасу ходу можуть допомогти зменшити стрес водіїв електромобілів. Ця робота пропонує стратегію прогнозування на основі моделі для оцінки енергоспоживання електромобіля. Оцінка враховує конкретні параметри електромобіля, а також топології дорожньої мережі, в якій працює транспортний засіб, і реальні умови руху. Представлена макромодель енергоспоживання електромобіля дозволяє використовувати доступні на типових картах веб-сервіси для отримання зведених даних в реальному часі. Дорожня мережа моделюється як зважений орієнтований граф, що адаптований до запропонованої моделі споживання енергії. Оптимізація пробігу досягається засобами алгоритму пошуку оптимального шляху, придатного для використання в реальному часі. Отриманий таким чином діапазон руху забезпечує покращену точність і надійність у порівнянні з середнім споживанням та на основі дистанційної стратегії.

Ключові слова: запас ходу; оцінка споживання енергії; електромобілі; суміжний граф; алгоритм найкоротшого шляху.